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CASCADING AIR POWER EFFECTS SIMULATION (CAPES)

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This research focused on modeling the behavior of specific dissident groups. In particular, it focused on explaining and forecasting sustained campaigns of dissdent violence by these groups. We ask: which variables should we monitor in terms of anticipating when groups will turn to campaigns of violence? We sought to specify models which examined the interactions of groups, governments, and the mass populace within various environmental contexts. To meet this objective, new data was collected on the behavior of groups and governments using autmated natural language processing techniques. New data on the attitudes of the masses and Arabic mass media were also collected using similar techniques. Using this data, we specified econometric models to explain and forecast the behavior of groups of interest. Each group was modeled on its own but each model contained similar sets of variables. The groups of interest studied were the Tamil Tigers, Moro Islamic Liberation Front, Bangladesh Chhatra League, the People's War Group in India, the Free Papua Movement in Indonesia, Hamas, Al Aqsa, Hezbollah, and the Palestinian Islamic Jihad.

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TABLE OF CONTENTS

1.0 EXECUTIVE SUMMARY 1

2.0 INTRODUCTION 3

3.0 THEORETICAL FRAMEWORK 5

4.0 YEAR ONE 10

4.1 Research Design 10

4.1.1 Case Selection 10
4.1.2 Descriptiono of the Data 11
4.1.2.1 Events Data 11
4.1.2.2 Structural Data 15
4.1.2.3 Sentiment Data 17
4.1.3 The Estimators and Modeling Strategy 18
4.1.4 Explanation of Graphs, Tables, and figures 19
4.1.5 Out-of-Sample Forecasting 22

4.2 Results 23

4.2.1 The Liberation Tigers of Tamil Eelam (LTTE) 24
4.2.2 Moro Islamic Liberation Front (MILF) 31
4.2.3 Bangladesh Chhatra League (BCL) 38
4.2.4 People's War Group (PWG) 45
4.2.5 Free Papua Movement or Organisasi Papua Merdeka (OPM) 51

4.3 Discussion of Results 60

4.4 Conclusion 61

5.0 YEAR TWO 66

5.1 Sentiment Data: Availability and Aggregation 66

5.2 Hostile Phases 71

5.3 Base Models All Groups 76

5.4 Sentiment Models All Groups 79

5.5 In-Sample and Out-of Sample Forecasting 94

5.6 Discussion 100

6.0 DATA APPENDIX 102

REFERENCES 104

LIST OF ACROYNMS 109

LIST OF FIGURES

Figure 1: Example of MILF Violent Activities and Hostile Phases ... 14
Figure 2: Example ROC Curves ... 20
Figure 3: Example Accuracy Plot over Time ... 22
Figure 4: Example Out-of-Sample Forecast Graph (MILF 1997-2006) ... 23
Figure 5: LTTE Violent Phases ... 24
Figure 6: LTTE Model ROC Curve ... 26
Figure 7: LTTE In-Sample Predicted Values over Time ... 27
Figure 8: Negative Binomial In-Sample Predicted Values for LTTE ... 28
Figure 9: Smoothed Negative Binomial Predicted Values for LTTE ... 28
Figure 10: LTTE Duration Model In-Sample Predicted Values ... 29
Figure 11: LTTE Logit Model Out-of-Sample Forecast ... 30
Figure 12: LTTE Out-of-Sample Duration Model Forecast ... 30
Figure 13: LTTE Out-of-Sample Duration Model Smoothed Forecast ... 31
Figure 14: MILF Violent Phases ... 32
Figure 15: ROC Curve for MILF ... 33
Figure 16: MILF In-Sample Predicted Values over Time ... 34
Figure 17: MILF Duration Model In-Sample Predicted Values ... 35
Figure 18: Negative Binomial In-Sample Predicted Values for MILF ... 36
Figure 19: MILF Logit Model Out-of-Sample Forecast ... 36
Figure 20: MILF Out-of-Sample Duration Model Forecast ... 37
Figure 21: Out-of-Sample Duration Model Smoothed Forecast ... 37
Figure 22: BCL Violent Phases ... 38
Figure 23: BCL ROC Curve ... 40
Figure 24: BCL In-Sample Predicted Values over Time ... 41
Figure 25: BCL Duration Model In-Sample Predicted Values ... 42
Figure 26: Negative Binomial In-Sample Predicted Values for BCL ... 43
Figure 27: BCL Logit Model Out-of-Sample Forecast ... 44
Figure 28: BCL Out-of-Sample Duration Model Forecast ... 45
Figure 29: PWG Hostile Phases ... 46
Figure 30: PWG ROC Curve ... 48
Figure 31: PWG In-Sample Predicted Values over Time ... 48

Figure 32: PWG Duration Model In-Sample Predicted Values 49
Figure 33 Negative Binomial In-Sample Predicted Values for PWG 49
Figure 34: PWG Logit Model Out-of-Sample Forecast 50
Figure 35: PWG Out-of-Sample Duration Model Smoothed Forecast 51
Figure 36: OPM Violent Phases 52
Figure 37: OPM ROC Curve 54
Figure 38: OPM In-Sample Predicted Values over Time 55
Figure 39: OPM Duration Model In-Sample Predicted Values (Smoothed) 56
Figure 40: Negative Binomial In-Sample Predicted Values for OPM 57
Figure 41: Smoothed Negative Binomial Predicted Values for OPM 57
Figure 42: OPM Logit Model Out-of-Sample Forecast 58
Figure 43: OPM Out-of-Sample Duration Model Smoothed Forecast 59
Figure 44: OPM Out-of-Sample Duration Model Smoothed Forecast with Box-Shaped Phases Shown 59
Figure 45: Causal Model of Military Training in India (1997-2006) 63
Figure 46 Average Time-Series Effects of US Military Exercises on Separatist Violent Events: India 1997-2006 64
Figure 47: Change in Separatist Violent Events per Month over the Duration of Military Training in India 2002-2006 64
Figure 48: Sentiment Availability by Source 66
Figure 49: IRT Scaling of Sentiment toward Hamas 67
Figure 50: MDS of Sentiment Sources toward Israel 69
Figure 51: MDS of Sentiment Sources toward Palestine 69
Figure 52: MDS of Sentiment Sources toward Al Aqsa 70
Figure 53: MDS of Sentiment Sources toward Hamas 70
Figure 54: MDS of Sentiment Sources toward Hezbollah 71
Figure 55: MDS of Sentiment Sources toward Palestinian Islamic Jihad 71
Figure 56: Al Aqsa Hostile Phases 73
Figure 57: Hamas Hostile Phases 74
Figure 58: Hezbollah Hostile Phases 75
Figure 59: Palestinian Islamic Jihad Hostile Phases 76
Figure 60: Al Aqsa Model 95
Figure 61: Al Aqsa Out-of-Sample Forecast 96

Figure 62: Hamas Model 97
Figure 63: Hamas Out-of-Sample Forecast 97
Figure 64: Hezbollah Model 98
Figure 65: Hezbollah Out-of-Sample Forecast 98
Figure 66: Palestinian Islamic Jihad Model 99
Figure 67: Palestinian Islamic Jihad Out-of-Sample Forecast 100

LIST OF TABLES

Table 1: Example Classification Statistics ... 21
Table 2: Model Results for LTTE Violent Phases ... 25
Table 3: LTTE Classification Results ... 26
Table 4: Model of MILF Violence ... 33
Table 5: MILF Classification Results ... 34
Table 6: Model of BCL Violence ... 39
Table 7: BCL Classification Results ... 40
Table 8: Model Results for PWG Violent Phases ... 47
Table 9: PWG Classification Results ... 47
Table 10: Logit Model Results for OPM Violent Phases ... 53
Table 11: OPM Classification Results ... 55
Table 12: Summary of Major Findings ... 60
Table 13: Distance Matrix of 5 American Cities ... 68
Table 14: Base Models for All Groups ... 78
Table 15: Al Aqsa Sentiment Models: Good Sentiment ... 80
Table 16: Al Aqsa Sentiment Models: Bad Sentiment ... 82
Table 17: Al Aqsa Aggregated Sentiment Model ... 83
Table 18: Hamas Sentiment Models: Good Sentiment ... 84
Table 19: Hamas Sentiment Models: Bad Sentiment ... 85
Table 20: Hamas Aggregated Sentiment Model ... 86
Table 21: Palestinian Islamic Jihad Sentiment Models: Good Sentiment ... 87
Table 22: Palestinian Islamic Jihad Sentiment Models: Bad Sentiment ... 88
Table 23: Palestinian Islamic Jihad Aggregated Sentiment Model ... 89
Table 24: Hezbollah Sentiment Models: Good Sentiment ... 90
Table 25: Hezbollah Sentiment Models: Bad Sentiment ... 91
Table 26: Hezbollah Aggregated Sentiment Model ... 92

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1.0 EXECUTIVE SUMMARY

Our project is a two-year effort focused on modeling the behavior of specific dissident groups. In particular we focused on explaining and forecasting sustained campaigns of dissident violence by these groups. We ask: which variables should we monitor in terms of anticipating when groups will turn to campaigns of violence? We sought to specify models which examined the interactions of groups, governments, and the mass populace within various environmental contexts. To meet this objective, new data was collected on the behavior of groups and governments using automated natural language processing techniques – in year one by Strategic Analysis Enterprises (SAE) and in year two by Social Sciences Automation (SSA). New data on the attitudes of the masses and Arabic mass media were also collected starting late in the first year using similar techniques. Using this data, we specified econometric models to explain and forecast the behavior of groups of interest (GOIs). Each group was modeled on its own but each model contained similar sets of variables.

In the first year, the GOIs were the Tamil Tigers in Sri Lanka, the Moro Islamic Liberation Front in the Philippines, the Bangladesh Chhatra League, the People's War Group in India, and the Free Papua Movement in Indonesia. We found that structural environmental variables had minimal impact on explaining and predicting sustained group violence. The key variables that did explain violent phase changes included government repression of the GOI and other competing groups, other competing groups' activities, and mass political attitudes. Specifically, violent activities by other groups in the recent past yielded a higher probability that the GOI would engage in a violent campaign. The repression of other groups also had either positive or curvilinear impacts on the likelihood that GOI would engage in a sustained violent campaign. By curvilinear we mean that at low and high levels of repression, the probability of violent activities is low, while moderate level of repression of other groups increased the likelihood that the GOI would engage in a sustained violent campaign. Government repression of the GOI also yielded curvilinear effects on the probability that the group would enter a hostile phase change. Our automated sentiment variables also had fairly consistent effects on the violent campaigns and activities of our GOIs. Societal support for the government decreased the probability that a GOI would engage in a violent campaign for four of our five groups. Moreover societal support for the dissidents increased the probability that a GOI would carry out a sustained violent campaign. These findings suggest that groups monitor the activities of the government, other competing groups, and mass attitudes of the public in making strategic decisions as to how to behave in the political arena.

Using this multi-competitive-actor framework, we generated econometric models to explain and forecast the behavior of GOIs. Our models classified, on average, 92% of the observations correctly across all five groups with a range of 87% to 97% accuracy. Moreover, our models had high positive and negative predictability. That is, they were able to distinguish between observations classified as part of violent campaigns and as part of non-campaigns. Moreover, our models did very well at forecasting violent phase changes out-of-sample. We also generated models capable of discerning the onset, duration, and cessation of violent campaigns with a high degree of accuracy. Overall, our results suggest that we can develop models capable of explaining and forecasting the violent behavior of dissident groups in various countries. Finally,

we took our analyses one step further by examining the impacts of United State (US) Diplomatic, Informational, Military, and Economic (DIME) action on the levers in our models to illustrate one fruitful avenue for future research. We show that we can model the first, second, and third order effects of US actions on group violence in order to uncover which strategies and tactics are useful in mitigating violent political conflict.

In the second year, the GOIs were Hamas, Al Aqsa, Hezbollah, and Palestinian Islamic Jihad. The sentiment data available for this analysis was in the form of counts of the number of "good" words and "bad" words reported by each source about a group of interest – a much less robust form than that used in year one. We modeled both good and bad sentiment toward groups of interest and found that both measures improve overall fit compared to models with no sentiment, by as much as 8 points for the Al Aqsa model but by only two or three points for the other groups. Overall, these sentiment data did not play a major role in explaining the ebb and flow of violent events by our GOIs. However, the report does not dismiss the utility of sentiment data writ large. SAE showed in year one and other studies that sentiment can play a large role in explaining variance in groups' violent behavior. In particular, the sentiment data for this study lacked context. In other words, the data represented news sources' sentiment rather than expressions by citizens, social actors, and other relevant actors. This complicated the modeling process because we had to first consider whether individual news sources were supportive or hostile toward Israel, Palestine, Lebanon, and the groups of interest. Moreover, some news sources did not report sentiment for the full time-span of analysis and it was necessary to aggregate similar sources together to extend the sentiment data over the full time-span. This appeared to be a successful strategy and increased the amount of data for modeling.

While we did not observe the large effects we had hoped, many of the relationships were statistically significant. More often than not, any increases in sentiment toward a group of interest increased the probability of a hostile phase. We might have expected that only good sentiment toward a group would embolden the group, however negative sentiment appears to operate in much the same way. The advertising axiom "any publicity is good publicity" may fairly accurately characterize this scenario.

The following sections detail our analyses, results, and conclusions.

2.0 INTRODUCTION

This project focuses on explaining and forecasting phase shifts in militant groups' behavior. Specifically, we examine the factors that lead groups to adopt and continue a campaign of violent political behavior. Campaigns or phases of violent political behavior consist of a series of sustained, planned, organized activities which utilize physical force to achieve benefits concerning the extraction and distribution of resources or values.[1] Our project uses econometric models to explain and forecast such campaigns carried out by five specific groups in five different countries.

We bring together several distinct domains of analysis (structure-, process-, group-, and attitudes- oriented) focused on the topic of political violence. To begin, previous research in this area has traditionally highlighted the structural conditions that affect the propensity of violent political conflict such as poor economies, highly ethnically fractionalized societies, weak democratic institutions, and highly populated areas. Other research has focused on the interactions of actors making decisions and their strategic, interdependent tactical decisions (e.g., violent, nonviolent, terroristic, and cooperative actions). It champions the idea that violence is a product of a series of joint-decisions that various actors make over time. A third approach emphasizes the effects that inter-group competition has on the behavior of groups. Finally, a fourth wave of scholarship emphasizes the effects of mass political support and how it alters the ebb and flow of political dynamics between organized groups and governments. In reality, actors in competition with one another for public political support make decisions within constrained environments. As a result, all four of these perspectives have merit yet few, if any, have integrated them to examine their effects in a single model of political violence. One reason is because of the challenge of trying to model these relationships and another is because of the dearth of data available to attempt such a feat.

Our analyses confront both of these challenges. First, our project uses coding schemes and software developed by prior National Science Foundation (NSF) and Defense Advanced Research Projects (DARPA) efforts to generate new data. We then bring this data together in a unified model for rigorous investigation. We collect new event data containing numerous actors' tactical choices culled from myriad text reports, structural data available in many publicly available data sources such as the World Bank Development Indicators Database, and automated sentiment data culled from text reports using a newly developed software program.

We then generated dependent variable series of campaigns of violent phases for five groups in five different countries using the events data containing information on each group's violent events. Our independent variables consist of the tactical choices of competing groups, the

[1] We define political behavior as any action taken by an actor to advance its political interests. By political, we mean issues that involve the authority to make decisions concerning the extraction and distribution of resources or values. We define violent actions as those which exhibit physical force. Violent actions include rioting, instances of large scale property violence, abductions or hostage takings, the use of unconventional force such as suicide bombs, improvised explosive devices, and/or armed combat, skirmishes, and clashes. Campaigns or phases of behavior consist of sustained, planned, organized activities to achieve an objective.

repressive practices of the government, the structural attributes of the environments in which each group operates and mass political attitudes (e.g., sentiment) directed towards the groups and the state. We then specify econometric models that examine the relationships among our independent variables and violent campaigns. These models explain and forecast the occurrence of such campaigns over time. We also supplement our analyses with different dependent variable specifications such as the duration of campaigns and the number of violent events per month to enhance the credibility of our models and bolster our findings.

Below, we elaborate on our theoretical framework and then describe our research design in more detail. Next, we report the results and conclude with the implications of our analyses and ideas for future research in this area.

3.0 THEORETICAL FRAMEWORK[2]

One way to study violent political conflict within countries is to focus on the structural conditions that impact the chance that a country will experience such phenomena. Another way is to analyze the behavioral relationships among parties to potential conflicts, how they make decisions, how such decisions impact other parties' decisions, and how the sequences of behavioral interactions escalate and de-escalate across various thresholds of violent political conflict. Or, as Harry Eckstein (1980) put it over 25 years ago, we can distinguish between "contingency" and "inherency" approaches to the study of violent conflict. The first perspective assumes that conflict is contingent on unusual or irregular conditions that cause disruptions in conventional politics. The contingent approach leads one to study the political, economic and social attributes of countries to explain variation in their conflict experiences. The inherent perspective assumes that violent political conflict emerges out of low-level contentious interactions among a set of political players. This approach leads researchers to focus on the conditional behavior of parties to conflict and how that behavior changes over time. While Eckstein laid out these two approaches in 1980, until recently the past 25 years have borne witness to few scholars taking the latter path. We hypothesize that this is because of the dearth of available data and the complexity involved in modeling multiple actors' behavioral interactions.

Prior to the turn of the century the study of intrastate conflict was much more focused on the former approach than the latter. While studying the political, economic, and social attributes of countries is a useful approach for understanding and highlighting general patterns of conflict, it is ill-suited to address conflict processes because such approaches "are essentially static 'input-output' or 'stimulus-response' type models, not dynamic models of interaction" (Moore, 1995). Charles Tilly (1985) argues that because "collective action is dynamic… its outcomes depend very strongly on the course of interaction." A recent wave of scholarship eschews the structural attributes approach and instead focuses attention on the escalation and de-escalation processes of political conflict instantiated by actors' strategic behavioral interactions.[3] A common thread running through this new generation of conflict scholarship is a shift from countries as the unit of analysis to the parties to the conflict and their behavior. This work focuses on competition between governments and various dissident groups over policy, control of the state, and—especially—the support of the population.[4]

This shift is critically important because it means that theory becomes much more useful to policy makers: the emphasis on conflictual parties leads this research to develop hypotheses about the hostile behavior of dissidents in response to government behavior and vice versa. By moving away from thinking about the impact of democratic vs. autocratic institutions, the size of Gross National Product (GNP)/capita, and the ethnic composition of society these scholars have begun to ask the following sorts of questions:

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[2] Much of the discussion in this section comes from Shellman's prior work in this area including but not limited to Shellman (2004a; 2004b; 2006a; 2006b). Some exact prose is taken from Moore and Shellman (2008) with Moore's permission (Shellman was primarily responsible for the writing and placement of the article).

[3] Recent reviews of this literature can be found in Davenport (2007) and Lichbach (In Press). Also see Shellman 2006a; 2006b).

[4] Note that Galula (1964) was writing about the importance of this issue back in the 1960's.

When does repression work? When does it backfire?
Why are some dissident groups so much more violent than others?
What event sequences lead to conflict escalation?
What are the effects of government countermeasures on dissidents' tactics?
What explains the ebb and flow of government-dissident behavioral exchanges?

Note that information about political institutions, economic output, and ethnic composition are of limited usefulness for answering these questions. Why? Because those characteristics of the country in which these conflicts unfold *do not change much over time*. To the extent that they change, they change rather slowly. As one recent paper put it "the factors analyzed in country level analyses are the same for a given country during war and peace, and are therefore incapable of predicting shifts from one period to the other." (Butler, Gates, & Leiby, 2005). To better understand such conflict processes, we must study the behavior of the parties to the conflict. And if we are going to study behavior, then it is surely reasonable to study it as purposive, strategic behavior that varies systematically in response to the behavior of other parties to the conflict.

To be sure, we have learned from the structural approach that characteristics of the state such as regime type, the economy, terrain, capabilities, and demographics like population and ethnicity are correlated with the level of political conflict we observe *across countries*. However, the structural attributes approach has not taught us much about conflict processes as they unfold *over time within specific countries*. For example, we know that a country with mountainous regions is more likely to experience an insurgency. Yet, knowing that Afghanistan is mountainous tells us little about when we are likely to observe peace or conflict in Afghanistan. That said, we are not arguing that we should disregard these important insights. Rather, the best scholarship should situate behavioral studies of conflict processes within a structural framework. And this is precisely what we do here.

We argue that intrastate conflict is *not* best characterized as something that countries catch (or experience). Instead the new generation of scholarship recognizes that governments often face multiple challengers fighting for the same cause and/or very different causes, and that these challenges vary across both space and time. As such, these theorists have been disaggregating the study of civil conflict across actors, space and time. [5] Civil conflicts often involve infighting among members or branches of the government (e.g., military coups in Nigeria) and often yield dissident group splits (e.g., the Moro Islamic Liberation Front emerged out of the Moro National Liberation Front). In other cases, multiple groups with heterogeneous preferences may interact with each other and even form alliances or coalitions (e.g., the Coalition Government of Democratic Kampuchea – comprised by the Khmer Rouge, the Front Uni National pour un Cambodge Independant, Neutre, Pacifique et Coopratif (FUNCINPEC) and Khmer People's National Liberation Front (KPNLF)). Other research has disaggregated actors and their behavior to demonstrate that both diplomatic and military intervention by third countries on behalf of dissidents or governments can have strong bearing on pushing parties to the table or escalating

[5] See Shellman, Hatfield, and Mills (2010) for an example.

violent activity.[6] In sum, intrastate conflict is comprised of many different parties with different motivations, who make a variety of decisions as to how to behave in both the short and long run. To answer questions like the ones listed above we need to adopt a disaggregated unit of analysis and account for the behavior of these different parties.

Second, civil conflicts rarely span an entire country's territory. Rather, they are often confined to sub-national regions based on certain geographic features that generate conditions favorable for conflict. Teams of researchers are making considerable progress pursuing this seemingly obvious point. For example, mountains or jungle provide cover for rebels to hide and wage guerilla campaigns. Resource rich zones abundant in minerals (e.g., diamonds) or other valuables (oil, etc.) may also contribute to reoccurring conflict.[7] Motives may also determine conflict locations. For example, recent research claims that separatist groups tend to fight away from the capital in order to make their territory autonomous, whereas insurgents aiming to overthrow the state tend to fight nearer to the source of the power – in the capital city or province where the capital is located.[8] Moreover, international borders can often provide refuge from governmental control, and this may cause conflict events to cluster near international boundaries which, in turn, can have important implications for neighboring countries (Salehyan & Gleditsch, 2006). The general point is this: if we wish to investigate theories that have a geographic element we need to abandon the country level of analysis in favor of a disaggregated spatial approach. Importantly, doing so will produce research with far more rich policy implications than we have seen prior to the emergence of this new generation of research.

Third, the unit of time over which one aggregates is consequential (Shellman, 2004a). Until recently most research has focused on the year as the unit of temporal aggregation. Marcellino (1999) explains that "temporal aggregation arises when the frequency of data generation is lower than that of data collection so that not all the realizations of the stochastic process… are observable." Yearly aggregation obscures the actions and reactions of actors in much smaller units of time such as monthly intervals. At what temporal units do dissidents and governments respond to one another? Surely the answer is: it varies. But just as surely the answer is *not*: annually! To focus on the kinds of questions that the new generation of civil conflict scholars is asking requires that we abandon annually aggregated data in favor of data collected over the unit of time in which they occur.

In the mid 1990s, Phil Schrodt revolutionized the collection of events data when he released the Kansas Events Data System (KEDS) computer program.[9] This program demonstrated that it is possible to use computers to code news reports to generate data about the behavior of dissidents toward governments, governments toward dissidents, government toward other governments, etc. Over the past 15 years the KEDS project has spawned a number of similar projects, and this technology has spilled over into a variety of other areas of political science as well.[10] Where

[6] See Moore (1995); Moore and Davis (1998); Gleditsch and Beardsley (2004); Thyne (2006).
[7] See Humphreys (2005); Ross (2006).
[8] See Buhaug and Gates (2002); Buhaug and Lujala (2005); Rød and Buhaug (2007).
[9] See Schrodt, Davis, and Weddle (1994).
[10] See, for example, Pennings and Keman (2002); Monroe, Quinn, Colaresi, Radev, Abney, Crespin, Shomer, Matsuo, and Hobolt (2007).

hundreds of hours of human labor were required to code such reports computers are able to produce such data in mere minutes. This has radically changed the information that is available to scholars. Further, the shift in conceptual and theoretical interests described above demand just such data.

Project Civil Strife (PCS), directed by Stephen Shellman, uses computerized coding technology to generate disaggregated data useful for testing the hypotheses advanced by the new generation of intrastate conflict researchers. The project directly confronts actor, spatial, and temporal aggregation by collecting information on multiple actors' behavioral interactions each day in various geographic locations. With respect to actors, PCS codes the behavior of just about any dissident or government group discussed in open source media reports. It codes individual's names and offices and even tracks individuals like Norodom Sihanouk in Cambodia who at different times of the conflict serve as a government official and then as a rebel leader. By disaggregating the state and the social and dissident actors, scholars and policy makers can examine interactions among multiple parties (See Shellman, Hatfield, & Mills, 2010). Project Civil Strife also disaggregates space (Shellman, 2008), time (Shellman, 2004a; 2004b), and tactics (Horne, Stewart, & Shellman, 2008).

Further, governments and dissident groups compete for the support of the public. In addition to disaggregating the study of political conflict into actors and their behavior, we also contend that support for actors' decisions and their tactics plays an important role in political and conflict dynamics. Mao Tse Tung (1966, 57) stated that "We must rely on the force of the popular masses, for it is only thus that we can have a guarantee of success." Che Guevara (1985, 50) followed by saying that "the guerrilla fighter needs full help from the people of the area. This is an indispensable condition…" and guerrillas must draw their "greatest force from the mass of the people." Lyndon Baines Johnson (1965) added "The ultimate victory will depend on the hearts and minds of the people." Finally, Field Manual (FM) 3-24 (2006, 1-28) states that "At its core, COIN [counterinsurgency] is a struggle for the population's support. The protection, welfare, and support of the people are vital to success. Gaining support and maintaining it is a formidable challenge." Stathis Kalyvas' (2006) recent book makes the importance of distinguishing among the government, the dissidents, and the public abundantly clear: he observes that death tolls in civil wars vary systematically depending on whether either the dissidents or the government can exercise authority over the town or whether the territory is actively contested by dissident and government troops. Mia Bloom (2005) makes an argument that groups compete with each other for popular support and engage in "outbidding" behavior (i.e., attacking more violently than the last group) in order to gain more support from the public. In the policy world, many argue that governments and dissidents are both trying to "win hearts and minds."

In short, we know that support from the masses impacts political violence and politics more broadly. Yet, empirical studies are limited by a dearth of data to test how policies and actions shape attitudes and beliefs and how such attitudes and beliefs affect various actors' strategies, tactics, and actions. Historically, polls were the only means to measure and include such indicators in models of politics. However, polls are infrequent, expensive, and complicated to carry-out in certain locations. As a result, sentiment is difficult to measure in near real time and across space (cities, towns, regions, countries, etc.). Recently, DARPA contracted Dr. Shellman

to generate an automated sentiment analysis software package that could take in millions of lines of text from news sources, blogs, and Diaspora sources and output aggregate measures of sentiment towards actors' actions, policies, and political events. Advances in linguistics, natural language processing, and technology allowed us to develop a prototype of a sentiment coder. In a recent DARPA seedling, we showed that our newly generated sentiment data closely mirrors polling data and performs well in models of politics, increasing various models' explanatory power. That is, our models which include sentiment better explain and forecast political behavior with less error than models which exclude such data. We have used that technology in this project and collected new sentiment data for our cases and analyses completed for this project.

In sum, we use these theoretical pillars as a starting point to build our models of violent campaigns. We carefully examine the interdependent choices of the state and dissident groups as well as the tactics of competing groups in our models. Furthermore, we include measures of the environment and contextual factors as well as measures of mass support in our models. The results are fairly robust models explaining the occurrence and duration of violent campaigns as well as forecasting such violent campaigns out-of-sample.

4.0 YEAR ONE

4.1 Research Design

In this section, we explain our case selection, describe our data sources, operationalize our concepts, and elucidate our modeling strategy.

4.1.1 Case Selection

SAE previously collected events data for 29 countries for the period 1997-2006 in the US Pacific Command (PACOM) Area of Responsibility (AOR). Given resources we obtained collecting data in this region, we wanted to concentrate on groups operating within these 29 countries. We also began this project working with Sandia National Laboratory. As such, we coordinated with the Laboratory so we could work on modeling the same groups. Our first criterion for group selection was that the group had to move in and out of at least two violent phases during our period of analysis (1997-2006). We required at least two violent phases because we wanted to be able train our model on the first phase and attempt to forecast the second phase. Another criterion had to do with our original partner on the project. Sandia focused on the rhetoric of groups so they desired to focus on groups that not only exhibited violent phases but also generated rhetoric in English for their analysis. This limited our sample to a few groups. We settled on examining the violent phase changes of the Moro Islamic Liberation Front (MILF) in the Philippines, the Liberation Tigers of Tamil Eelam (LTTE) in Sri Lanka, and the Bangladesh Chhatra League (BCL) student organization. After we realized that Sandia was not going to have success with all these organizations and were going to focus on different organizations, we added to our analyses the People's War Group (PWG) in India, and the Free Papua Movement or Organisasi Papua Merdeka (OPM) in Indonesia to round out our sample.

These groups differ in motivation and intent as well as in their historical use of violence. The separatist group known as the Tamil Tigers (LTTE) may have been considered the most violent group on Earth until May 2009. They started a campaign for autonomy and independence in 1983 and were the innovators of the modern suicide attack. The PWG is more of an insurgency organization than a separatist organization. The PWG closely aligns its tactics with Mao and the idea that revolution can occur through peasant insurrection. Their goal is to install a "people's government" through a "people's war." The MILF is more in line with separatist, autonomous intentions as they seek to set-up an Islamic state in the southern Philippines. The OPM is also a separatist organization wishing to establish its own state separate from Indonesia. Finally, we examined the BCL, a student organization closely tied to the Awami League which is one of the two major parties in Bangladesh. This organization is traditionally nonviolent and took part in many of the historical democratic movements. However, of late during the 1990's and 2000's the BCL has engaged in political violence and bared the brunt of political violence carried out by the other major party, the Bangladesh Nationalist Party (BNP), either as opposition or as the government. In all we modeled three separatists groups, an insurgent group, and a student organization. Some of these groups have religious roots whose practices contain religious overtones such as the Moro Islamic Liberation front, while other groups like the LTTE and OPM are more ethnically grounded with little religious fervor underlying their goals. The People's war party grounds its goals and tactics in a Maoist/Communist ideology.

In sum, we have a mix of ethnic, religious, pro-democratic, and communist groups in our sample. Given that we have heterogeneous groups, if we find similar relationships between our independent variables and dependent variables we can rule out social, political, and social differences across groups as explanations (Manheim & Rich, 1995, 253). If, however, we do find gross differences in relationships across groups, we can only speculate whether motivation, culture, group characteristics (e.g., religion, ethnicity, etc. or environment e.g., the country's economy, regime type, etc.) is responsible for those differences. Therefore, we attempt to control for some of those differences by including some environmental variables in our models.

4.1.2 Description of the Data

We bring four main theoretical insights to our project. We desired to model the (1) behavioral processes of the actors within (2) contextual environments. In addition, we wanted to examine (3) inter-group competition and how (4) support for governments and dissidents translated into actions. We operationalized our behavioral processes and group competition concepts using events data. We included many structural characteristics using data from the World Bank Development Indicators database and we used our new software, Pathos, to generate sentiment data which we describe in more detail below. Our unit of analysis is the group-month. We discuss each source of data and how we operationalize our concepts below.

4.1.2.1 Events Data

Event data, "day-by-day coded accounts of who did what to whom as reported in the open press," offer the most detailed record of interactions between and among actors (Goldstein, 1992, 369). They are particularly suited to test how actors act and react to one another since they are a systematic collection of interactions among the actors in a particular domain. Each event data record contains four important pieces of information: "actors" taking actions ("events") against "targets" on a given "date." Most event data sets focus on international conflict and cooperation between and among countries (e.g., the Cooperation and Peace Data Bank (COPDAB), the World Events Interaction Survey (WEIS), and KEDS. These data prove useful in foreign policy studies and studies of reciprocity in international relations (Goldstein & Pevehouse, 1997; Goldstein & Freeman, 1990; 1991). Fewer event datasets address intranational conflict (e.g. Intranational Political Interactions (IPI), the Violent Intranational Conflict Data Project – VICDP, the European Protest and Coercion dataset, and the Protocol for the Assessment of Nonviolent Direct Action (PANDA) project).[11] While many of these data prove useful in studies concerning the repression-dissent nexus (Francisco, 1995, 1996; Moore, 1998, 2000; Shellman, 2006a; 2006b) and the domestic-international conflict nexus (Moore & Davis, 1998), each of these datasets has its strengths and weaknesses.

Existing internal conflict datasets focus on particular cases, actors, or event types and use a variety of coding methods. To begin, VICDP (the precursor to IPI) includes 5 cases spread out across the globe, IPI mainly focuses on Latin America (with a few exceptions) and Francisco's

[11] Two of these studies (IPI and VICDP) were collected, in part, by my dissertation advisor, Will H. Moore (see http://garnet.acns.fsu.edu/~whmoore/dataprojects.html). I worked as a research assistant on the IPI project. See http://lark.cc.ukans.edu/~ronfran/data/index.html for Ronald Francisco's European data. See http://www.wcfia.harvard.edu/ponsacs/research/PANDA_IDEA.htm for the PANDA project description.

data focus on Europe.[12] The PANDA project began examining Europe as well and was superseded by the Integrated Data for Events Analysis (IDEA), which covers international and intranational conflict across the whole world (but only a portion of the data is publicly available and the coverage of internal actors and groups is less than desirable).[13] With respect to actors, VICDP, IPI, and Francisco's protest and coercion data code multiple actors. However there are some limitations. While Francisco codes multiple actors (students, Muslims, ethnic Bulgarians, democracy movements, etc.), the project ignores dissident-dissident interactions and ethnic conflict. Of all projects previously mentioned VICDP and IPI code the most actors; however, most of the dyads in which the government is an actor, the general population or unspecified social actors are coded as the targets. While this poses no problems to two-actor models of government-dissident interactions, it is impossible to disaggregate the "general population" without going back to the original stories and recoding the events to students, workers, ethnic groups, etc. Moreover, not all the datasets code both conflict and cooperation. Francisco's data only analyze protest and repression. This scheme leaves out high level conflictual events like armed conflict and guerrilla attacks and cooperative events such as positive and supportive statements, peace talks, and negotiated settlements. PANDA only codes nonviolent contentious events and focuses less on cooperation. The only datasets that code both conflict and cooperation are IPI and VICDP. Finally, the datasets differ with respect to how the data were generated. Human coders collected the IPI and VICDP datasets, while machines coded the majority of the PANDA and Francisco datasets. Previous criticisms of event data center on coding inconsistencies and biases (Andriole & Hopple, 1984; Laurence, 1990). In addition, the costs of coding event data have reduced the rate of data collection. Yet, those problems have been mitigated by machine-readable data sources and machine coding. Schrodt and Gerner (1994) and King and Lowe (2003) show that machine-coded and human coded data are very similar and produce the same inferences in time series studies. Moreover, machine-coded data are replicable and consistent. They are also less time consuming to collect compared to human coded data.

The events data for this project come from Shellman's PCS dataset. They differ in various ways from the aforementioned datasets and combine the strengths of those data collection efforts by coding conflict and cooperation, multiple actors, and using machines and automated coding software to eliminate inconsistencies, coder fatigue, and coding time. Moreover, the data focus on a new region (South and South East Asia) and code some additional variables. PCS uses a modified version of Text Analysis by Augmented Replacement Instructions (TABARI), developed by Phil Schrodt, to generate domestic political event data.[14] TABARI uses a "sparse-parsing" technique to extract the subject, verb, and object from a sentence and performs pattern matching using actor and verb dictionaries.[15] In short, TABARI matches words from an electronic text file (news story) to words contained in the actor and verb dictionaries and assigns a corresponding code to each actor and verb. It also records the date. Finally, we have modified the source code to code locations of events. Thus, in addition to coding actors and verbs, TABARI pattern matches cities and regions and assigns corresponding codes.

[12] Some focus on Latin America and Korea; and there is less than one year of Burma data (1988).
[13] See http://vranet.com/IDEA/. IDEA is produced by Virtual Research Associates, Inc.
[14] See http://raven.cc.ukans.edu/~keds/index.html for information on the KEDS and TABARI projects.
[15] TABARI recognizes pronouns and dereferences them. It also recognizes conjunctions and converts passive voice to active voice (Schrodt, 1998).

While most event data sets code events from a single news source,[16] we code events from multiple news sources. Reeves, Shellman, & Stewart (2006) and Davenport & Ball (2002) show that media bias influences the scientific inferences we draw from statistical models which analyze data from a single news source. Potentially, language, coverage, style, and characterization by a source can influence the way an event is coded or even if it is coded at all. Schrodt, Simpson, & Gerner (2001, 36) write

> Reuters and AFP are comparable in terms of the general patterns of events they report. They are not, however, identical sources of information…Reuters provides denser coverage in the Balkans… What seems to be important here is not only that AFP differs in style from Reuters, but that there are regional differences in AFP as well. This suggests that sometimes Reuters is in the right place at the right time, and sometimes AFP.

These findings suggest that source bias deserves more attention. Schrodt et al., (2001) go on to suggest the possibility of creating multiple source chronologies and some of the expected complications. In the end they conclude it is feasible and should be done. The US PACOM AOR dataset contains information from over six million news reports (over 25Gb of English and translated foreign language text) from over 75 different news agencies. We used multiple sources for our project including national sources like *The Statesman* (India), *Philippines Daily Inquirer*, and *The Jakarta Post* (Indonesia). We then created multiple source chronological datasets.

Machine coded data are only as good as the dictionaries. Each of the actor dictionaries is customized for each case. We first generate an initial actor list by researching the case. We then use an automated software program to identify actors in texts and add actors to the actor dictionary when they are absent. We also record the dates for regime changes, government and dissident leadership changes, leaders' exit and entrance methods (election victories, coups, revolutions, etc.), and dates of the births and deaths of dissident groups/political parties using various sources.

Our verb dictionary is a modified KEDS verb dictionary. Verbs and verb phrases are assigned a category based on the Conflict and Mediation Event Observations (CAMEO) coding scheme.[17] However, KEDS has introduced new codes in addition to those used by McClelland and the WEIS project. Most of these are borrowed from the PANDA project.[18] So we build on those codes. However, while many of the KEDS verbs are relevant to intranational conflict, the file is missing many verbs that appear in stories on civil conflict like "protest." We will use the Goldstein (1992) scale and the KEDs additions to assign weights to the event codes.

We had previously collected aggregate quarter-year event data for generic dissident actors in Sri Lanka, the Philippines, Bangladesh, India, and Indonesia for another government project –

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[16] For example, early KEDS data and IPI data come from *Reuters*, while later KEDS data come from *Agence France Presse*. WEIS data come from *The New York Times Index*.
[17] See http://web.ku.edu/~keds/cameo.dir/CAMEO.CDB.09b5.pdf.
[18] See http://www-vdc.fas.harvard.edu/cfia//pnscs/panda.htm for information on the PANDA project.

Integrated Crisis Early Warning System sponsored by DARPA. For this project, we collected new event data for each individual group of interest as well as some of their competitors. We also collected events data for each of the governments, which include police and military activities. Given that our unit of analysis is the group/country-month, we aggregated our data for each group in each country for each month.

Operationalization of Violent Phase Changes, Group Behavior, & State Repression

<u>Dependent Variable: Violent Phase Changes</u>: Our goal is to assess *when* specific GOIs shift their behavior towards sustained violent campaigns of action. As such we desire a time series of each GOIs behavioral actions. Our events data contain information about who is doing what to whom and serve as a natural indicator for measuring a group's actions over time.

To operationalize violent campaigns we plotted the group's violent actions overtime. Violent actions include riots, kidnappings, armed clashes, bombings, suicide attacks, and attacks resulting in deaths and/or property damage. After plotting the frequency of these actions over time, we looked to see where there were sustained acts of violence. In some cases this was easier to spot than in others. Groups like the LTTE seemed to be violent most of the time, but there were clear periods when violence peaked and stayed at high levels before returning to "normal" levels of violence. Other groups like the MILF in the Philippines sustained two clear-cut violent campaigns during our time period. In general groups had to carry out violent tactics for more than 2 months in a row at levels higher than their *normal* (mean, median, and/or mode) levels of violence. An example of denoted hostile phases overlaid on the violent activities of one of our GOIs, the MILF, is depicted in Figure 1.

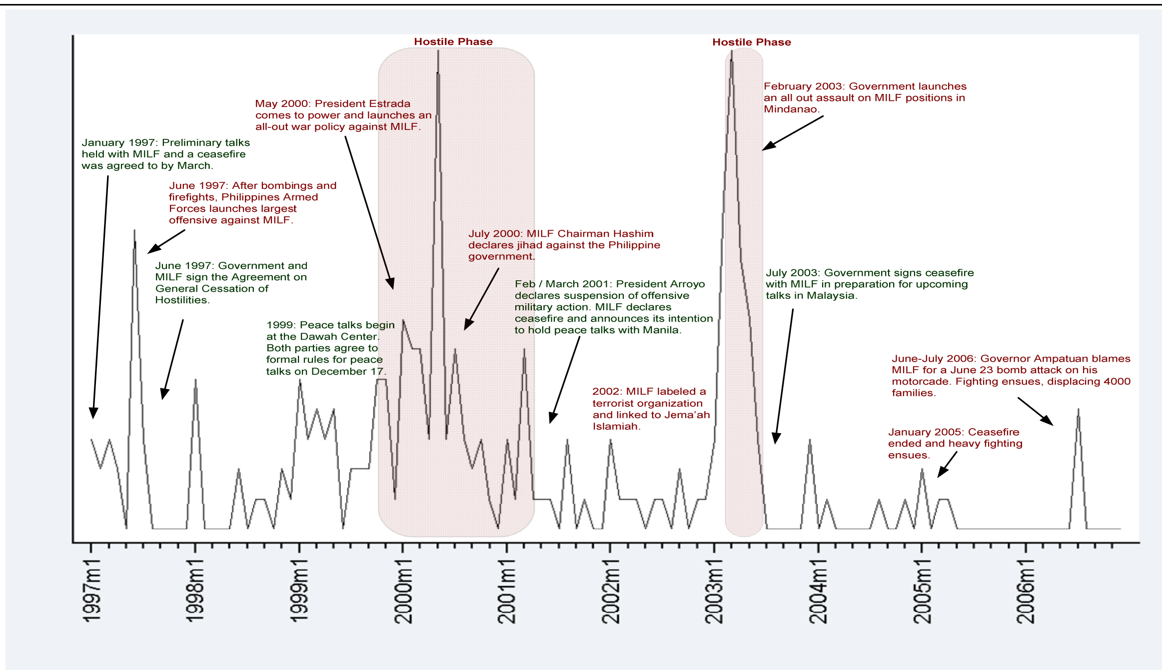


Figure 1: Example of MILF Violent Activities and Hostile Phases

Our main dependent variable is a dichotomous variable in which the variable takes on a value of 1 if the GOI is engaged in a violent phase of behavior and a value of 0 if the group is not in a violent phase of behavior. We created a second "duration" indicator which counts the number of months a hostile phase lasts. Finally, we used the raw violent event count for each GOI and modeled its properties as well.

State Repression: For our independent behavioral variables we created several indicators from our events data. A detailed description of each variable definition is in our Data Appendix (Section 6.0). First, we created variables representing the government's activities. We scaled all of the government's hostile activities using the CAMEO scale.[19] We then totaled those scaled values for each month. Many argue that high and low levels of repression yield low levels of dissent because there is nothing to dissent when repression is low and it is difficult to dissent when repression is high. However, at medium levels of repression there is opportunity and desire. That is repression may yield increases in violence at lower levels but such effects fade and actually become negative at higher levels of repression (inverted-U effect). To test these effects, we include squared terms in our model. If our hypothesis is supported, the non-squared term should be positive and significant and the second squared term should be negative and significant. As repression increases so does dissent up to a point at which dissent begins to decreases as repression increases towards its highest levels. Dissent should reach its highest levels under moderate repressive conditions.

Competing Group's Activities: We researched the groups in close competition with the GOI and we created time-series of their activities as well for each model. For example, we examined the New People's Army (NPA) activities in the model of MILF violent phase changes. We mostly concentrated on the other groups' hostile and violent activities. We created variables resembling our state repression variable by scaling the group's hostile activities and totaling them up by each month. We also simply counted the number of violent actions by each group in each month. Finally, for countries like India and Indonesia where there are too many groups to model separately, we created an aggregate indicator of all other competing groups such as all the groups in India vying for Independence or autonomy not including the group of interest. Our hypothesis that emerges out of the group competition literature is that because groups compete over resources as one group increases its violent activities, other groups in competition should also increase their violent activities. Thus we expect the competitive group's hostile and violent activities variables to yield positively signed and statistically significant coefficients. For example, in our MILF model, we would expect the coefficient on NPA violence to be positive and significant.

4.1.2.2 Structural Data

As we discussed above in our theoretical section, we think the best scholarship situates behavioral variables within contextual environments. That said, contextual variables create a couple problems for our research design.

[19] See http://web.ku.edu/~keds/cameo.dir/CAMEO.SCALE.txt for information on the scale and its values.

First, contextual variables are best used when modeling several cross-sectional units or in our case groups within the same model. In our design, we are modeling individual groups' actions as separate time-series.

Second, the contextual variables available for us to use in our models have several limitations. Most "environmental" indicators are only collected annually such as Gross Domestic Product (GDP), the number of imports and exports, foreign direct investment, etc. However, groups do not act in annual units. Moreover, these variables do not vary much overtime and our goal is to predict changes in behavior over time. As stated above, contextual variables best explain spatial variation or variation across countries as opposed to variations across time because they rarely change much and are often averaged or totaled across an annual unit. Our analysis for this project is the monthly behavior and so contextual variables at the annual level may not provide much explanatory and/or predictive power.

Perhaps an example best illuminates our first two arguments. Suppose we are trying to estimate the impact of government repression on Tamil Tigers' behavior in Sri Lanka and the PWG behavior in India in separate models. If the effects are both positive, statistically significant and relatively the same size, we would conclude that context does not matter much in amplifying or suppressing that relationship. Furthermore, if we find that repression is a key variable to forecasting a violent campaign then structure does little to increase our predictive power. If however, the estimated effects differed more substantially across groups and environments, we would not be able to make any claims about context without adding in contextual variables to the model. Perhaps in these instances contextual variables would yield important inferences about how they affect levels of violence.

Finally, we were able to collect some structural variables such as consumer prices and unemployment rates that are reported in monthly intervals and vary across our temporal units. However, they were not available for all of our countries in our sample, so we were unable to include them in every model.

We collected over 200 variables from the World Bank's Development Indicators Database but due to missing data problems and econometric problems only a few of these made it into our models. We discuss our econometric problems in more detail below but in short many of the macro-structural variables that were significant in the training data over fit our models and caused our out-of- sample predictions to generate many more false positives than we deemed acceptable. Foreign direct investment and the number of imports and exports as a percentage of GDP were the structural variables most useful in our models.

In addition to the annual country-year World Bank variables we were able to collect some monthly data on consumer prices, consumer food prices, and unemployment rates for a few of the countries from the International Labor Organization's LABORSTAT's database.[20] As we noted before, however, these were not available for all countries in our sample.

[20] See http://laborsta.ilo.org/.

4.1.2.3 Sentiment Data

The current state of sentiment analysis is in its infancy stages and is prone to many drawbacks. First, the majority of sentiment analysis focuses on how the writer feels about such phenomenon (e.g., how a reviewer or critic feels about a movie). Many researchers have developed tools to analyze how an author from a website (e.g., media, or blog) perceives politics. They use a bag of words (BoWs) technique to calculate the number of positive and negative words appearing in a specific story, blog posting, thread, or forum. While this is useful information, the sentiment is not attributable to a specific person and is difficult to tie to specific policies and actions. In short, the actor responsible for the sentiment and the target of the sentiment is often missing. If we want to know how certain types of people feel about a government policy or action, we cannot directly glean this information from such a strategy. While the approach is useful in understanding a particular author's opinions, it cannot measure how alternative actors feel about policies, actions, and/or political actors. We desire to know who is saying what about who and/or what. That is, we desire to code what we refer to as "utterances." An utterance is a complete unit of speech in spoken language. We want to know what various leaders of organizations and groups, social actors, and ordinary citizens are saying about government and dissident policies and actions. We can then break these utterances down and analyze them for meaning and interpret them within context.

We apply research in linguistics on discourse analysis, pragmatics, and speech acts to analyze strategic interactions among governments, dissidents, and the citizenry within countries. Pragmatics is the study of the way the use of language relates to the extra-linguistic context and thereby enables speakers to communicate more than that which is explicitly stated. From a pragmatic point of view, there are three main components of a communication. To begin, locution means the semantic or literal significance of the utterance. The second component is illocution or the intention of the speaker. The last component of a communication, perlocution, refers to how the locution was received by the listener and its subsequent effects.

Our key theoretical insight is that these three dimensions, locution, illocution, and perlocution, apply to political actions and reactions whether or not they use language. We contend that political actions such as calls for policy change, nonviolent protests, government repression, and terrorist attacks all contain three components of communication, a literal meaning, an intended meaning, and an interpreted meaning and/or effect. When these three components are out of balance with one another, miscommunication can occur. Its occurrence can yield unexpected and unintended actions and consequences. One of our goals in this project is to be able to explain and predict perlocutions (events) from locutions (utterances/speech acts).

Sentiment analysis based on vocabulary is well known, however, a more structured kind of sentiment analysis with more understanding of the semantics of the events being described remains absent from the current literature and technologies. Pathos began to fill that gap. Our focus on utterances and speech acts identifies specific actor's opinions as distinct from the mere intent or stance of the writer, and ties it back to event understanding. Previous work in this area lacks this ability.

The primary difference between our dyadic sentiment data and events data are the sentiment verbs (verbs identified as those conveying sentiment). As such, we developed a new sentiment verb dictionary. This new dictionary has over 800 verbs and verb phrases. Each of these sentiment verbs was rated on a scale from negative ten to ten (similar to the method CAMEO scale). Our coding engine, like TABARI, also uses actor dictionaries to identify the actor taking the action or expressing the sentiment as well as the target of the action receiving the action or the sentiment.

We're most interested in exploring the relationships between GOIs, the government, and the masses, so we focused on social actors which we defined as any citizen not party to a government leadership position or violent dissident group. As far as targets, we focused on the government and dissident groups at large. Each expression was rated on a -10 to +10 scale. We then averaged and summed the directed-dyadic scaled expressions. In sum, we created monthly aggregate measures of social actors' mean expressions towards governments and towards dissidents. Our measures in this study are not disaggregated across groups as our technology is not yet well developed for such disaggregation as of the time of the collection of these data. Therefore, we view the sentiment data as aggregate support for dissident and government activities. We are currently improving our technology to disaggregate sentiment across groups for future work.

4.1.3 The Estimators and Modeling Strategy

We modeled each group as its own time-series. Given that our main dependent variable is a nominal two-category variable (a group was in a violent phase or not) we employed a logistic regression modeling approach. The model performs a maximum-likelihood calculation that produces estimated parameters which have the highest probability of producing the observed data set. For our duration variable we experimented with Tobit regression where the series is bounded on both sides (e.g., 0 and 24 in terms of the number of months a hostile campaign has taken place), but ultimately simple Ordinary Least Squares regression techniques performed better. Finally, we modeled our count data (e.g., the frequency of each GOIs violent events) using a negative binomial estimator. Scholars frequently turn to either the Poisson or the negative binomial distribution when analyzing count data that are not normally distributed. A Poisson regression model is appropriate if one assumes that the probability of any given event is independent of any other event in a given unit of time (King, 1989; Long, 1997, chapter 8). In our case, we would need to assume that the probability of any given attack in a given month was independent of any other attack in that same month. Obviously, such an assumption is too strong as our goal is to model campaigns of violence which we assume are coordinated and as a result dependent on one another. Moreover, we argue that groups respond to a single information set (i.e., the behavior of government, the competing groups, the economy, etc.) and that groups' tactical decisions are linked via a common set of information. Thus, the appropriate distribution in such circumstances is the negative binomial distribution. The model includes a parameter, α, which enables one to estimate the extent to which the events influence one another within each

observation.[21] Our theory implies that α will be positively signed and statistically significant. In each case, α is positively signed and statistically significant.

In prior analyses, we ran models containing (a) only structural/Political, Military, Economic, Social, Infrastructure and Information Systems (PMESII) variables, (b) only behavioral variables, (c) only sentiment variables, and (d) all three sets of variables and, as suspected, the best models contained all three sets of variables. However, once we examined the out-of-sample forecasts we uncovered that the structural variables were over fitting the model. Why would this be the case? The structural variables don't change much overtime, but the conflict levels do. So while we were able to estimate an effect of say GDP on violent activities for a sub-set of the data that effect was carried through as a constant effect across the future time period. If violent activities were also constant there would not be a problem, but they are not and so the average constant effect for the subsample of data does not predict well out-of-sample into the future. This supports our point that while structural variables measured at the annual level may be useful at explaining variation across space (countries) they do not do well at explaining variation across time. It is often the case that the contextual factors for a given country are the same during periods of violence and periods of relative peace and cooperation. As a result, many are powerless in predicting phase shifts. We had to remove many of the annual variables from our models once we assessed their out-of-sample performance. The behavioral and sentiment variables tended to have the most explanatory and predictive power. In the end, we estimate the same model in terms of the independent variables on three different dependent variables.

All of the independent variables in our models are lagged at least one month. We lag our variables because we want to be able to utilize our models to forecast violent campaigns and violent actions by each GOI. In some cases, groups react with fairly short-run memory. That is, their actions depend heavily on their most recent experiences and interactions. However, some groups tend base their actions off less recent experiences and interactions. Such groups act with fairly long-run memory. That said, of our variables were lagged more than three months (one quarter) with the exception of our annual indicators. We increased our lag lengths only when they improved both the in- and out-of-sample forecasts. Last we also note that NONE OF OUR MODELS CONTAIN LAGGED DEPENDENT VARIABLES. While such variables can be useful in fitting a curve, they tend to lack theoretical rigor and soak up a lot of variance. That said, we did test their utility from time to time and we are happy to report that it was rarely if at all the case that a lagged dependent variable obtained statistical significance in our fully specified models. Our other variables tended to do so well as a collective whole we did not need to introduce them anyway.

4.1.4 Explanation of Graphs, Tables, and Figures

Following the estimation stage, we compute Receiver Operating Characteristic (ROC) curves which tell us how well our model fit the observed data. The ROC Curve plots two important pieces of information on a graph: sensitivity and 1- specificity. *Sensitivity* is the proportion of True Positives. High sensitivity is required when early diagnosis and treatment is beneficial

[21] See King (1989, 764-9) for a detailed explanation of why the negative binomial model is useful for this sort of argument.

(e.g., eruptions of mass violence). *Specificity* is the proportion of True Negatives of all negative cases in the population. High specificity is important when the treatment or diagnosis is harmful to the actor (e.g., harsh repression to stop violence). Figure 2 plots three separate sample ROC curves on the same graph. A ROC curve demonstrates several things:

1. It shows the tradeoff between sensitivity and specificity (any increase in sensitivity will be accompanied by a decrease in specificity).
2. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the test (e.g., the green curve in Figure 1).
3. The closer the curve comes to the 45-degree diagonal of the ROC space, the less accurate the test (e.g., the red line in Figure 1).
4. The area under the curve is a measure of *Accuracy*– the overall fit of the model. Specifically, it measures how well the model can discriminate 1's and 0's.

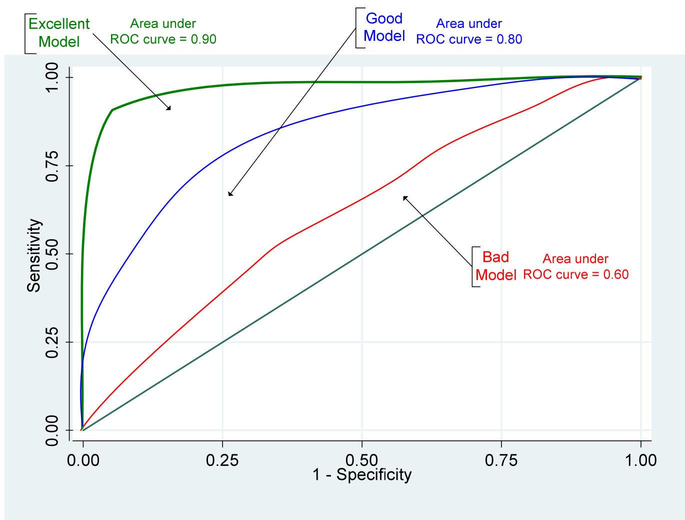


Figure 2: Example ROC Curves

For each logit model, we depict a ROC curve to show how well the model fits the data. Our goal in modeling these data is to maximize both specificity and sensitivity, not just overall accuracy.

In addition to ROC curves we also report the number of 1's predicted correctly, the number of 0's predicted correctly, the number of 1's incorrectly predicted, and the number of 0's incorrectly predicted (Table 1). In this example, 8 total observations were misclassified out of 108. Four were classified as 0's when they were actually 1's and four were calculated as 1's when they were actually 0.

Table 1: Example Classification Statistics

```
Logistic model for hostilephase

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |        19             4  |         23
     -     |         4            81  |         85
-----------+--------------------------+-----------
   Total   |        23            85  |        108

Classified + if predicted Pr(D) >= .5
True D defined as hostilephase != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   82.61%
Specificity                     Pr( -|~D)   95.29%
Positive predictive value       Pr( D| +)   82.61%
Negative predictive value       Pr(~D| -)   95.29%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)    4.71%
False - rate for true D         Pr( -| D)   17.39%
False + rate for classified +   Pr(~D| +)   17.39%
False - rate for classified -   Pr( D| -)    4.71%
--------------------------------------------------
Correctly classified                        92.59%
--------------------------------------------------
```

To show how these predictions play out over time, we devised bar graphs showing the actual violent phase points as well as the predicted violent phase points along a time series plot (Figure 3). A hostile phase *point* is a data point indicating violent activities during a hostile phase. The blue bars in the figures below show the actual hostile phase points, while the red bars illustrate predicted hostile phase points. When a red bar is stacked on top of a blue bar, the model correctly predicted the actual hostile phase data point (true positive). A blue bar by itself reveals where the model failed to predict a hostile phase point but there actually was such a hostile phase ongoing at that time (false negative). A red bar with no blue bar reveals where the model predicted a hostile phase point that did not occur (false positive). No bar indicates that the model did not predict a hostile phase point and there was no hostile phase point (true negative). For example, Figure 3 shows that the model correctly predicted 19 of the 1's (red bars stacks on top of blue bars) and 86 of the 0's (no bars shown). On the other hand it shows that it incorrectly predicted 0's for one of the actual 1's (blue bars only) and incorrectly predicted two 1's where there were no violent phase data points (red bars only). Overall, the model is over 97% accurate. It also predicts 95% of the 1's correctly (sensitivity or recall) and 97% of the 0's correctly (specificity). Below we report the results for our models using tables like Table 1 and figures like Figure 2 and Figure 3.

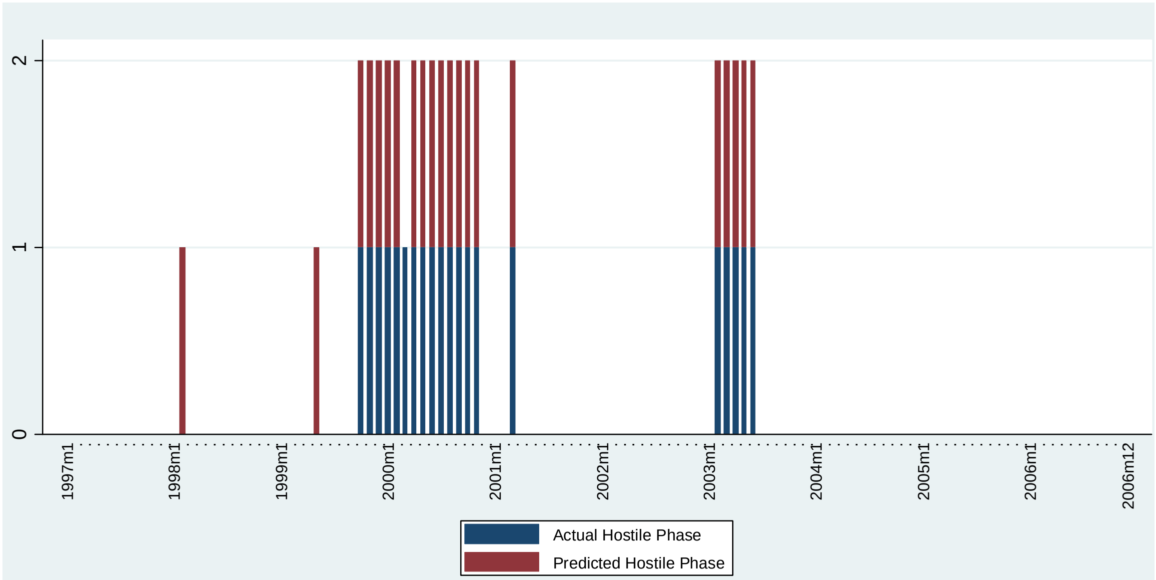


Figure 3: Example Accuracy Plot over Time

4.1.5 Out-of-Sample Forecasting

In addition to being able to explain phase changes we were more interested in whether our models were useful in predicting phase changes. Our strategy here was to train the data on approximately half of the sample or where there was a break in hostile phases and then use the model to forecast ahead in time to the next phases of violent activity. The model is deemed acceptable if it can forecast fairly well out-of-sample. We also experimented with windowing where we would select only a portion of the data and forecast another portion of the data. For example we would select observations 20-80 and forecast observations 81-120 and then select observations 40-100 and forecast observations 101-140, and so on and so on. Essentially, we wanted to know if our model's parameters varied across time and if so, how did that effect forecast. While there were certainly differences in parameter estimates across the different time periods, all in all, the models performed within an acceptable range in terms of their forecasts when comparing them to each other. We demonstrated these characteristics in a couple of our monthly status reports over the course of the project.

To determine how well the model forecasts into the future we plotted similar graphs to the one displayed in Figure 3 but we differentiated the in-sample predicted values (red) from the out-of-sample forecast values (green). Figure 4 shows an example of such a plot. Specifically, Figure 4 shows that our model predicts the second phase of violent activities very well by predicting all four 1's correctly and a couple sporadic false positives in 2004 and 2006. We argue that a good model will generate predicted values in clusters around the true phases of violent activities. If the model predicts such clusters of 1's around true 1's and a few sporadic 1's where there are not true 1's, the model is deemed to be accurate. An analyst would be trained to only look for clusters of predicted 1's as a sign of potential hostile phase changes in the future.

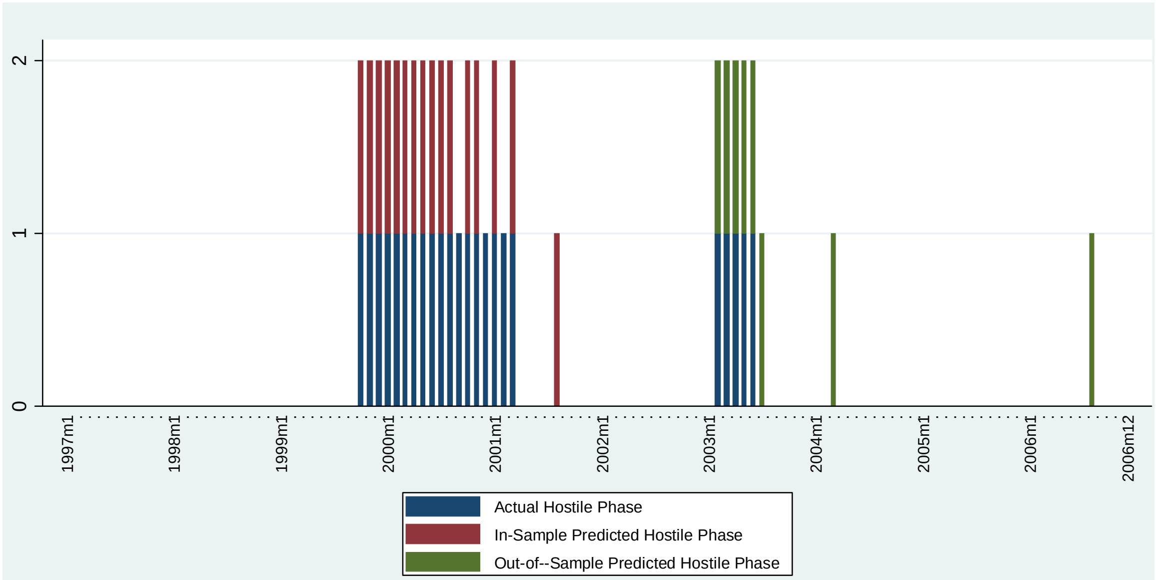


Figure 4: Example Out-of-Sample Forecast Graph (MILF 1997-2006)

4.2 Results

Herein we present the best in and out-of-sample models for each group. We remind the reader that we have completed much data collection and specified numerous models before settling on the models presented below. We also stress that the best out-of-sample model might not be the best in-sample model and vice versa. We focused on generating stable, well fitting models. By stable we mean that the parameters were stable both in and out-of-sample and that the in-sample and out-of-sample predicted probabilities fit the true data well in both instances.

While there are some differences across models, there exists a core set of variables present in each model that time after time produced stable estimates with high explanatory and predictive power. The core variables consistent with our theory include (1) at least one other competing group's violent activities, (2) government repression, (3) societal sentiment towards the government and (4) societal sentiment towards the dissidents. In many other models, levels of foreign direct investment and the percentage of imports and exports as a percentage of GDP also contributed explanatory and predictive power. Finally, when data were available on food prices and unemployment at the monthly level, those variables also exhibited fairly good explanatory and predictive power.

Below we review the results for each group we modeled. We spent the majority of time modeling the LTTE, the MILF, and students in Bangladesh. Once we had established models for these three groups we then applied similar models to three other groups in hopes that our core models would also apply well to additional organizations. Those groups included the PWG, and the OPM. With minor tuning, the core models explained and forecast violent campaigns by other

organizations well. We discuss each group's model and results below in turn and then summarize the similarities and differences across each group's model and results.

4.2.1 The Liberation Tigers of Tamil Eelam (LTTE)

The LTTE is one of the most lethal, organized terrorist organizations in the world. It began its campaign for a separate Tamil homeland in 1983 and is noted as the group which innovated the modern suicide attack. Figure 5 shows the number of violent attacks carried out by the LTTE over the period 1997-2006.

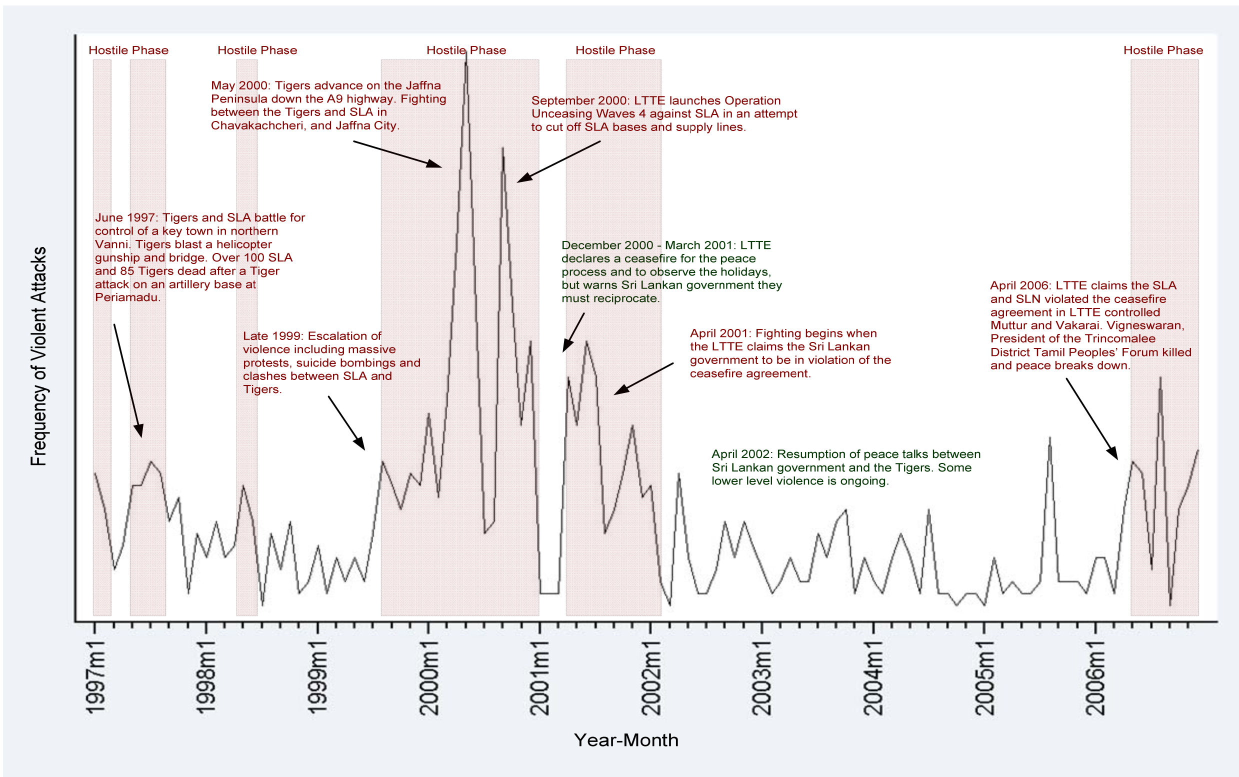


Figure 5: LTTE Violent Phases

The Tamil Tigers went through three longer periods of violence in 1999 through the beginning of 2001, in early 2001 through the end of the year, and then again in mid to late 2006. There were a couple of other spikes in violence which are also coded as violent periods even though these did not last too long – two months at the beginning of the series, and in early 1998 for example. Table 2 presents the results of the model of the Tamil Tigers. The most important variables are state repression, societal sentiment directed towards the government and Foreign Direct Investment (FDI). Increased FDI decreases the probability of sustained hostile activities as more investment helps the economy of the country. Repression (both the non-squared and squared term) yields a curvilinear effect on the probability that the Tamil Tigers engage in a hostile campaign of violence. That is, low levels of violence increase the probability of violence to a point and then decrease such probability. We also included a second lag of repression because

the Tamil Tigers seemed to base their current actions on aggregate state repression levels from the last two months. In terms of societal sentiment, our model showed that as sentiment towards the government grows stronger, the probability of the Tamil Tigers engaging in a violent campaign decreased. This shows that as more people support the government (i.e., the government wins more hearts and minds), the probability of violence subsides. Societal sentiment towards the dissidents had no statistically significant impact. The variable representing the Karuna' groups activities are also not statistically significant. The Karuna group is a splinter group that formed a political party and ultimately joined the government in fighting the Tamil Tigers. So it is not so much a competitive group as it is a partner with the government. As a result most of the variance was explained by the government repression variables. Finally, the food prices variable was not statistically significant either. That said, the model provided a better fit to the data by including the non-significant variables in the model.

Table 2: Model Results for LTTE Violent Phases

Independent Variable	*Coef.*	*Std. Err.*	*Sig*[a]
Food CPI (lagged 1 month)	-2.19047	1.798935	
FDI (lagged 1 year)	-0.92566	0.674562	*
Other Major Group's Violent Activities (Karuna group lagged 1 month)	0.097707	0.085443	
Government Repression to Main group (lagged 1 month)	0.066878	0.023449	***
Government Repression to Main group^2 (lagged 1 month)	-0.00016	7.16E-05	**
Government Repression to Main group (lagged 2 months)	0.031578	0.01045	***
Societal Sentiment towards Government (lagged 1 month)	-0.25657	0.118235	**
Societal Sentiment towards Dissidents (lagged 1 month)	0.07698	0.111182	
Constant	7.591385	9.160717	
Wald Chi-Square	43.28	_	***
N	108	_	_
Pseudo R^2	0.52	_	_

[a] *=.10, **=.05, ***=.01 significance level – one-tailed tests.

The model performed very well both in and out-of-sample. To begin, Figure 6 shows that the ROC curve fits the data very well given that it contains over 94% of the area under the curve. Table 3 shows model correctly classified 87% of the values of the dependent variable. Out of 108 observations, the model misclassified 14 observations. It generated 9 false negatives and 5 false positives. Both the sensitivity and specificity scores are fairly high in that the model is able to classify 76% of the true positives correctly while classifying 93% of the true negatives correctly.

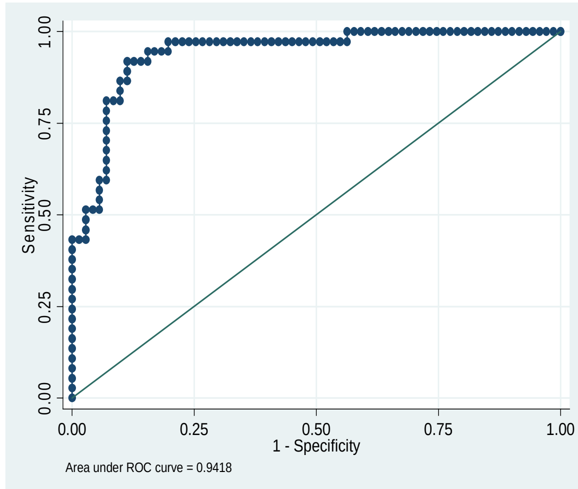


Figure 6: LTTE Model ROC Curve

Table 3: LTTE Classification Results

Classified	True D	True ~D	Total
+	28	5	33
-	9	66	75
Total	37	71	108

Classified + if predicted Pr(D) >= .495
True D defined as hostilephase2 != 0

Sensitivity	Pr(+| D)	75.68%
Specificity	Pr(-|~D)	92.96%
Positive predictive value	Pr(D| +)	84.85%
Negative predictive value	Pr(~D| -)	88.00%
False + rate for true ~D	Pr(+|~D)	7.04%
False - rate for true D	Pr(-| D)	24.32%
False + rate for classified +	Pr(~D| +)	15.15%
False - rate for classified -	Pr(D| -)	12.00%
Correctly classified		87.04%

When examining the temporal plot of the predicted values in relation to the actual values in Figure 7, one can see that the model does well at picking up on the trends and correctly classifying the majority of hostile phase observations near one another and identifying the chunks of time when there either is or is not a violent campaign taking place. Moreover, Figure 7 shows that the model picks up the break in hostile activities at the beginning of 2001 after intense fighting and then again fairly successfully anticipates the next violent phase. It also does well at not generating false positives during the relatively peaceful stretch of time from 2002 through early 2006.

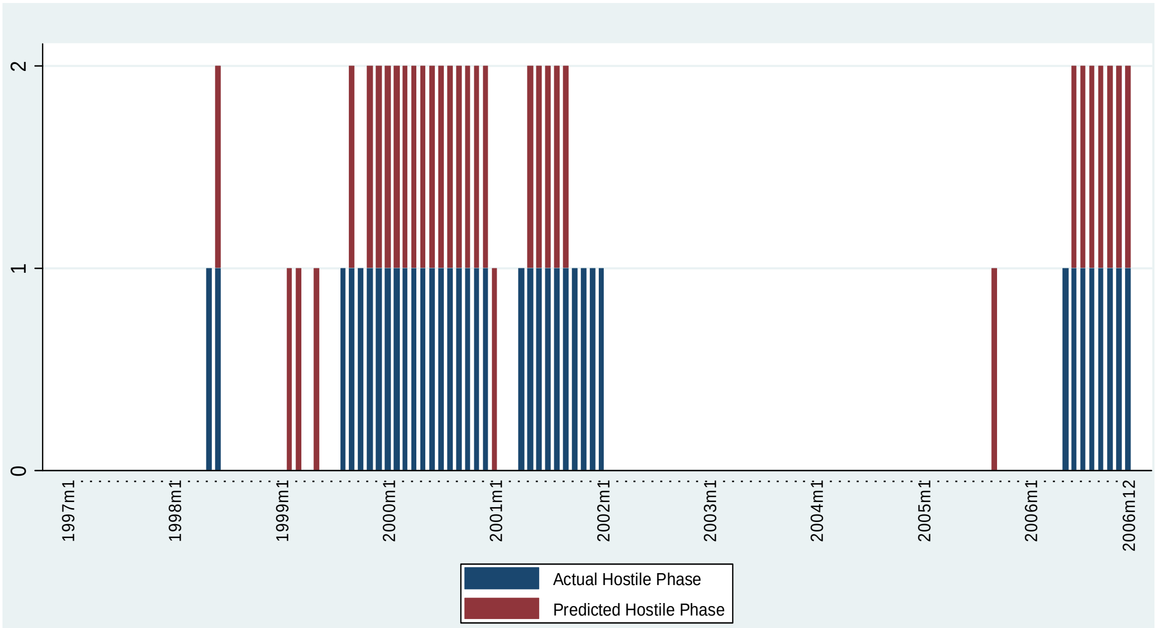


Figure 7: LTTE In-Sample Predicted Values over Time

In addition to the phase model, we also modeled the frequency of attacks in each month carried out by the LTTE using the same independent variables. As one can see from Figure 8, the model does well at estimating the general trends in the time-series and models well the average increases and decreases in the number of attacks each month. The predicted values and the actual values are correlated at .75. Figure 9 smoothes those trends out a bit by taking a moving average of the predicted values to highlight the ability of the model to capture the average level of the series over time.

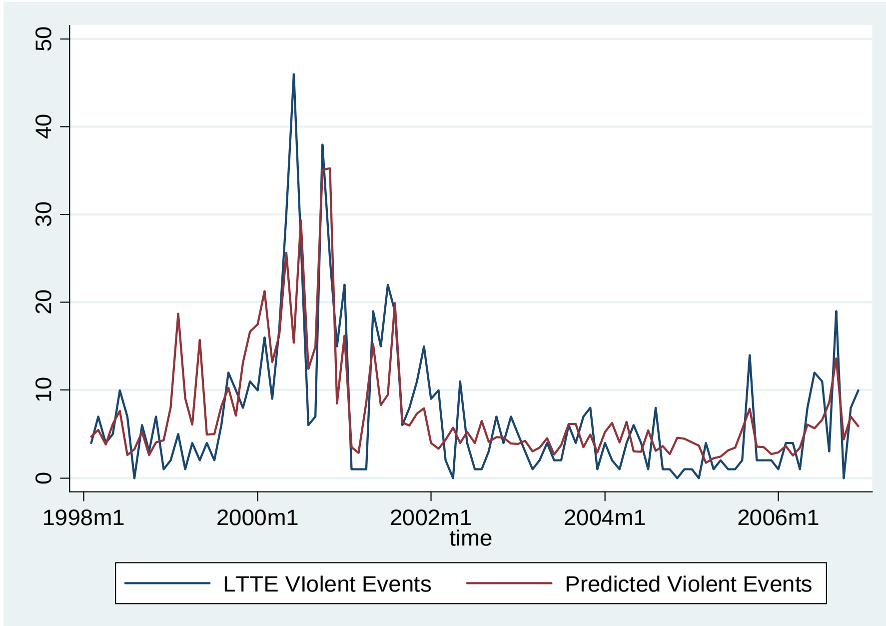


Figure 8: Negative Binomial In-Sample Predicted Values for LTTE

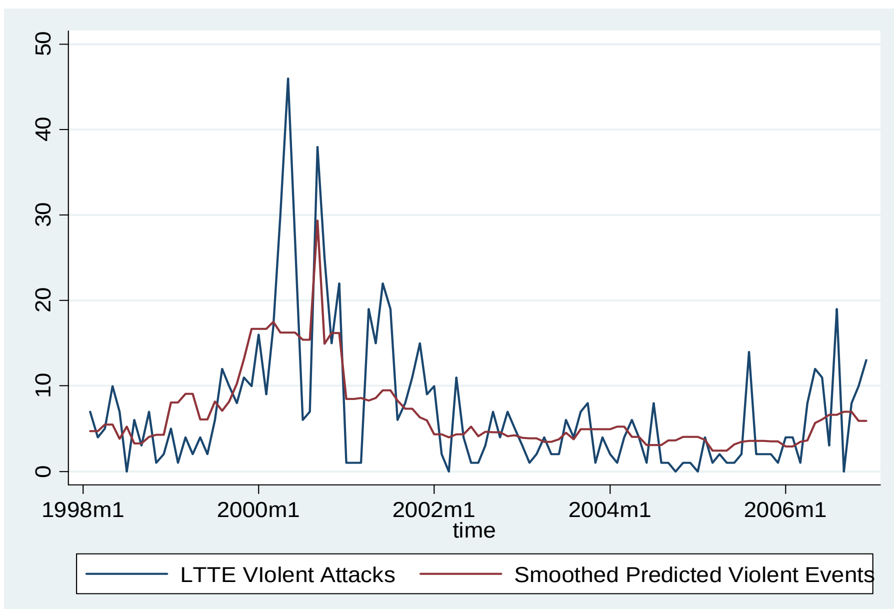


Figure 9: Smoothed Negative Binomial Predicted Values for LTTE

Moreover, we wanted to assess the ability of the model to estimate the duration of a violent campaign or phase. Figure 10 shows the results of our duration model. Our duration dependent variable is simply a count of the number of consecutive months that a campaign is ongoing. For example, the second LTTE campaign we coded, and really first major campaign, lasts 17 months before subsiding in mid-2001. The red fitted line shows that our model is able to track duration fairly accurately as it moves up and down in tandem with the count of the duration of each

campaign. In fact, the values of the predictions and the values of the actual series correlate at 80%.

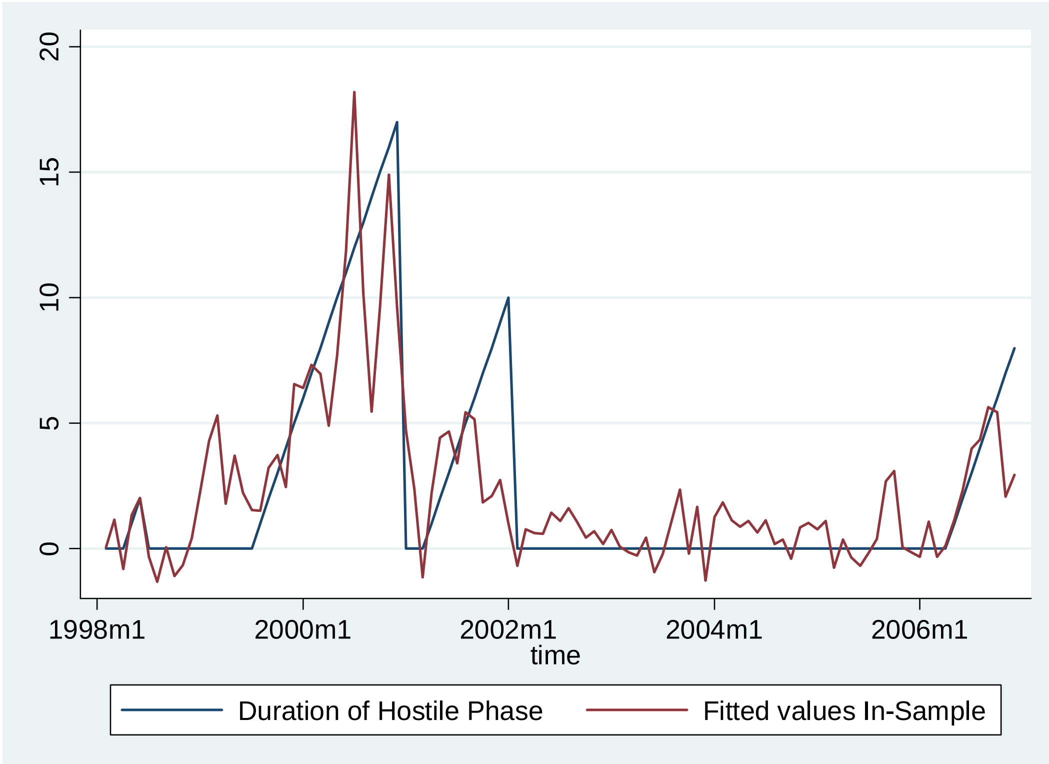


Figure 10: LTTE Duration Model In-Sample Predicted Values

Finally, we wanted to generate out-of sample forecasts of the various dependent variables in order to assess how well our model fit the out-of-sample data. Figure 11 plots our out-of-sample forecasts for the LTTE's last hostile phase. We essentially stopped our training data soon after the third hostile phase that we coded and generated predictions into late 2002 through 2006. Our model did an excellent job at being able to forecast the beginning and duration of the last hostile phase we collected data on. It produced only three false positives out of 60 observations (5%) and correctly predicted all eight 1's we coded as a collective violent campaign. Figures 12 and 13 show the results for our out-of-sample duration models. Figure 13 provides smoothed estimates again by taking a moving average across the predicted values. Both Figures 12 and 13 illustrate that the model is able to forecast the beginning, end, and duration of violent campaigns by the Tamil Tigers.

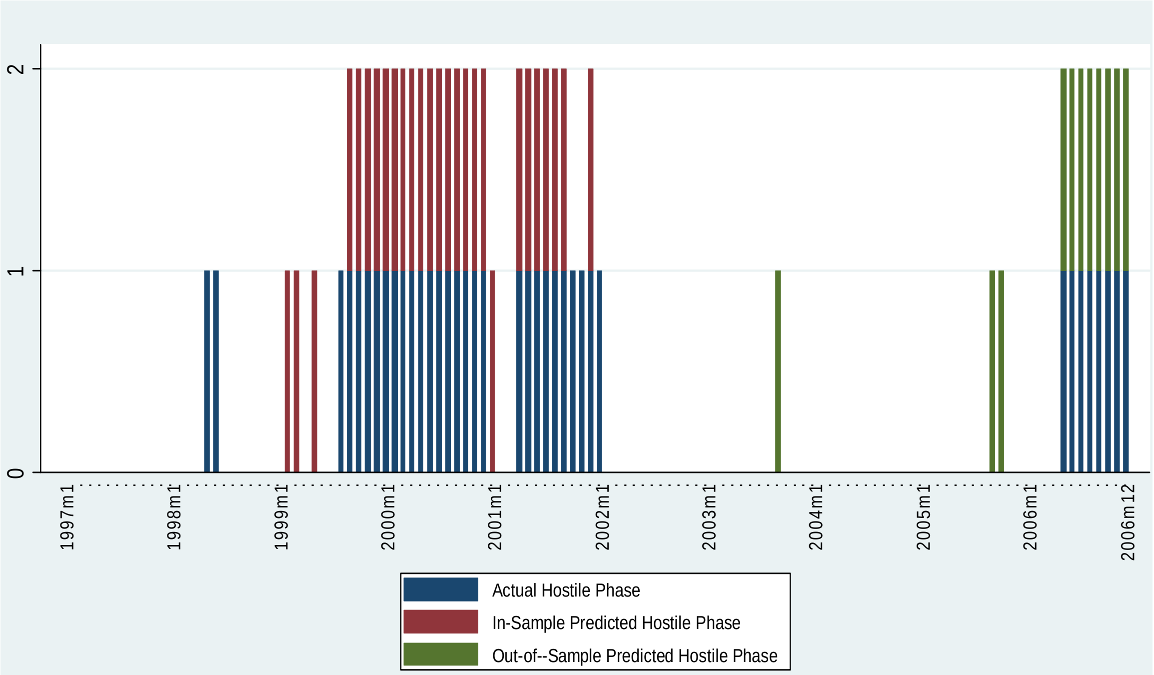


Figure 11: LTTE Logit Model Out-of-Sample Forecast

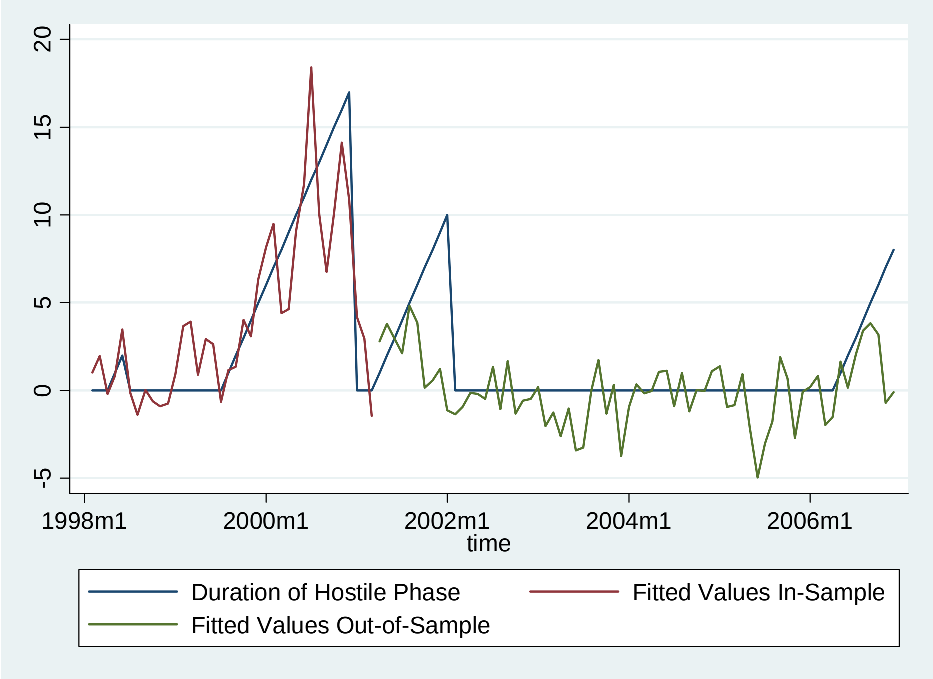


Figure 12: LTTE Out-of-Sample Duration Model Forecast

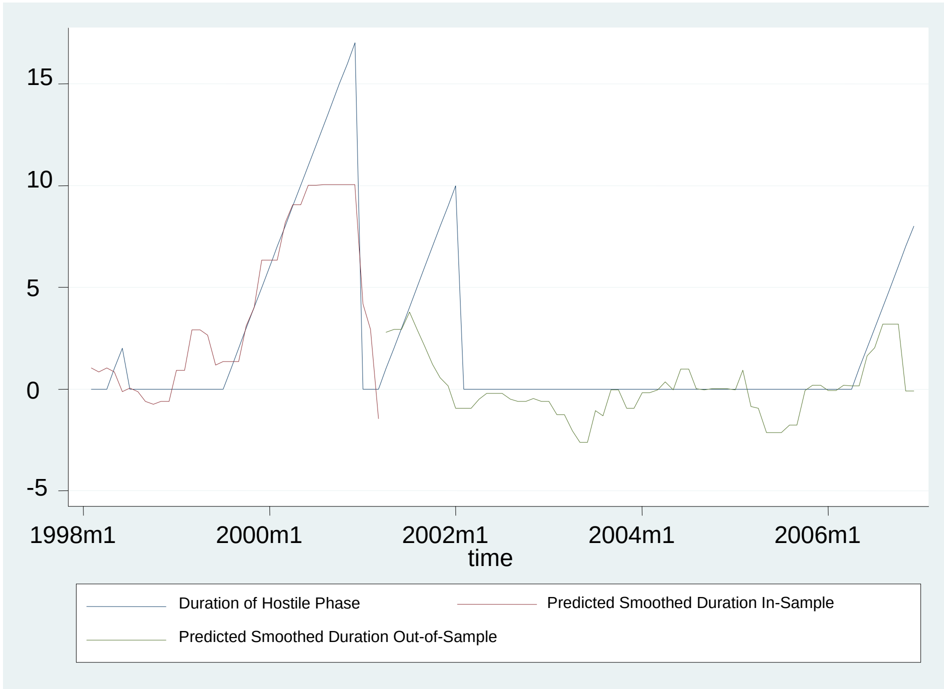


Figure 13: LTTE Out-of-Sample Duration Model Smoothed Forecast

Overall, our model of the LTTE across all three dependent variables performs exceptionally well. It is able to pick up the onset and cessation of sustained violent campaigns both in and out-of-sample with high sensitivity and specificity.

4.2.2 Moro Islamic Liberation Front (MILF)

The next group we chose to analyze is the MILF operating in the Philippines. While the group engaged in intermittent violence from time to time, Figure 14 illustrates that the MILF undertook two clear-cut phases of violence during our period of study. One occurs mostly throughout the year 2000 and the other shorter stint of violence occurs in early 2003.

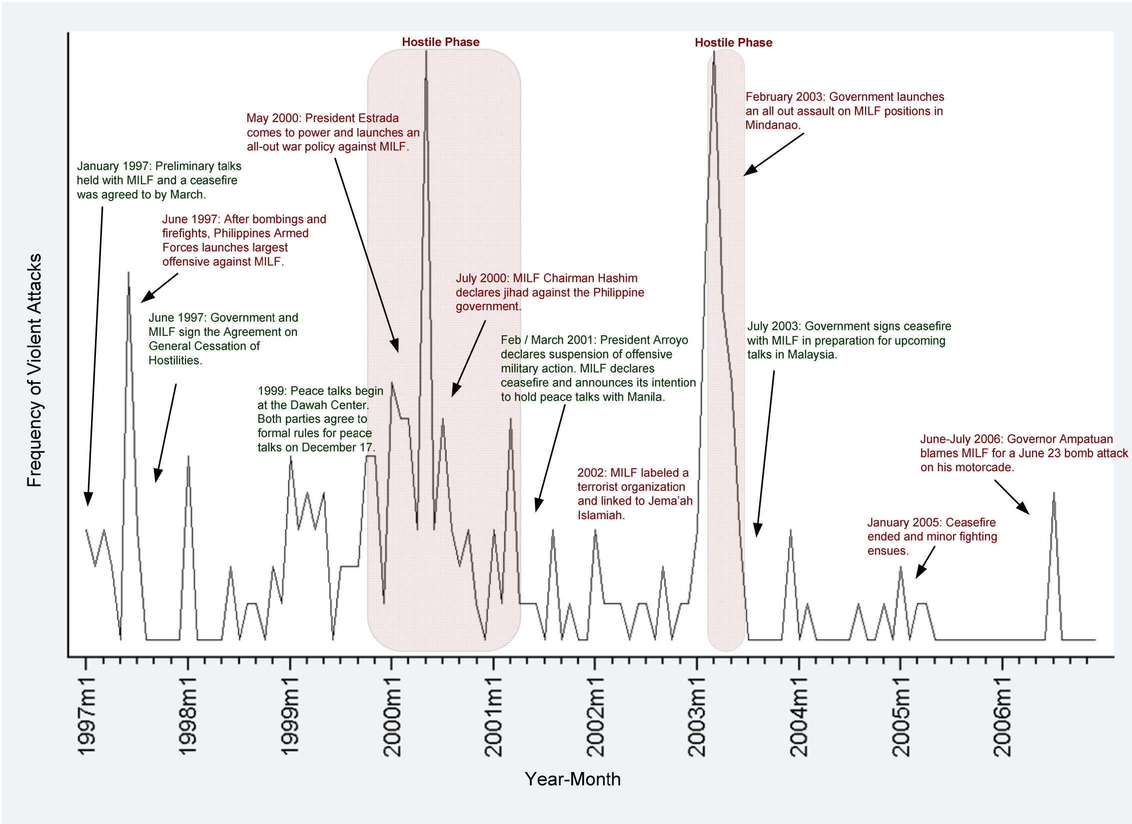


Figure 14: MILF Violent Phases

Our core model combines economic environmental indicators of monthly unemployment and annual FDI levels as well as the usual repression indicators and sentiment variables. The model also includes a measure of another competitor's hostile actions – the NPA. Table 4 shows that unemployment increases the probability that the MILF engages in a hostile campaign, while FDI decreases such likelihood. Our repression indicators have their hypothesized curvilinear effect much like we found with the LTTE. The difference with this model is that repression yields a curvilinear effect at a two month lag and a lag of one month prior. The NPA is essentially the armed wing of the communist party in the Philippines and operates in rural areas. It attempts to generate resources by forcing businesses, schools, and individuals to pay taxes. When entities default, violence usually ensues. The NPA has been largely contained and downsized in terms of its resources over the last 10 years or so especially since 9/11. However, both Maoist organizations compete for the support of the population. Mia Bloom (2005) suggests that groups oftentimes try to one up each other in terms of their violent activities to achieve additional support for their organization. If the hypothesis is supported we should see that the NPA variable is positive and statistically significant. We do in fact observe such a relationship in Table 4. Finally, both societal sentiment indicators are statistically significant. Positive sentiment towards the government, as was the case with the LTTE, decreases the likelihood of violence, while positive sentiment towards the dissidents increases the likelihood that the MILF engaged in a violent campaign. Overall, our model is an excellent model. The ROC curve depicted in Figure 15 shows that it covers 99% of the area under the curve. Moreover, Table 5 shows that our model

classifies correctly 97% of the observations, only misclassifying 3 of 108 observations. Both the sensitivity and specificity scores are very high in that the model is able to classify 95% of the true positives correctly and 98% of the true negatives correctly.

Table 4: Model of MILF Violence

Independent Variable	*Coef.*	*Std. Err.*	*Sig*[a]
Unemployment Rate	2.176852	1.425913	*
FDI	-2.25446	0.912469	***
Other Major Group's Violent Activities (NPA lagged 1 month)	0.110128	0.056497	**
Government Repression to GOI (lagged 1 month)	1.098516	0.481894	***
Government Repression to GOI^2 (lagged 1 month)	-0.0104	0.00463	***
Government Repression to GOI (lagged 2 months)	1.084761	0.509321	**
Government Repression to GOI^2 (lagged 2 months)	-0.01068	0.005083	**
Societal Sentiment towards the Government (lagged 1 month)	-0.56551	0.424015	*
Societal Sentiment towards the Dissidents (lagged 1 month)	0.668211	0.510139	*
Constant	-45.7675	25.3111	
Wald Chi-Square	51.19	_	***
N	108	_	_
Pseudo R^2	0.84	_	_

[a] *=.10, **=.05, ***=.01 significance level – one-tailed tests.

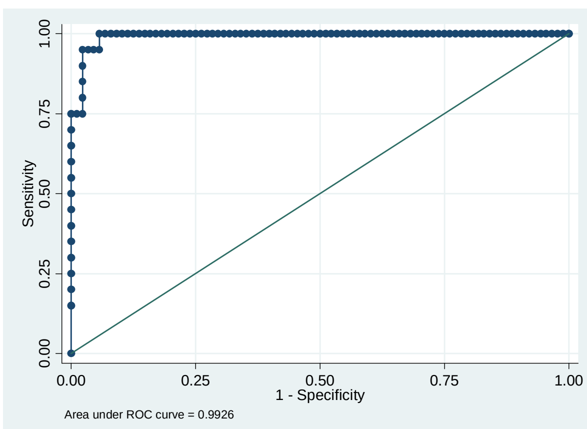


Figure 15: ROC Curve for MILF

Table 5: MILF Classification Results

Classified	True D	True ~D	Total
+	19	2	21
-	1	86	87
Total	20	88	108

Classified + if predicted Pr(D) >= .5
True D defined as hostilephase2 != 0

Sensitivity	Pr(+| D)	95.00%
Specificity	Pr(-|~D)	97.73%
Positive predictive value	Pr(D| +)	90.48%
Negative predictive value	Pr(~D| -)	98.85%
False + rate for true ~D	Pr(+|~D)	2.27%
False - rate for true D	Pr(-| D)	5.00%
False + rate for classified +	Pr(~D| +)	9.52%
False - rate for classified -	Pr(D| -)	1.15%
Correctly classified		97.22%

Turning attention towards the ability of the model to fit the data overtime, we examine Figure 16. Figure 16 shows that the model almost perfectly predicts the two major hostile phases carried out by the MILF during our period of analysis. It also shows two intermittent false positives. Again the model has the ability to differentiate sustained violent campaigns from random instances of violence. Figure 17 shows the output from the duration model. Again, the predicted values track well with the duration variables over time. The model predicts two clear sustained violent phases. That said, the model predicted false positives just prior to the second campaign. We note that the government links MILF to Jemaah Islamiyah – a major global terrorist organization with goals of establishing a caliphate across South and South East Asia. At this time, there are a few violent events but they did not fit our criteria of sustained violence nor were there many violent activities in any given month.

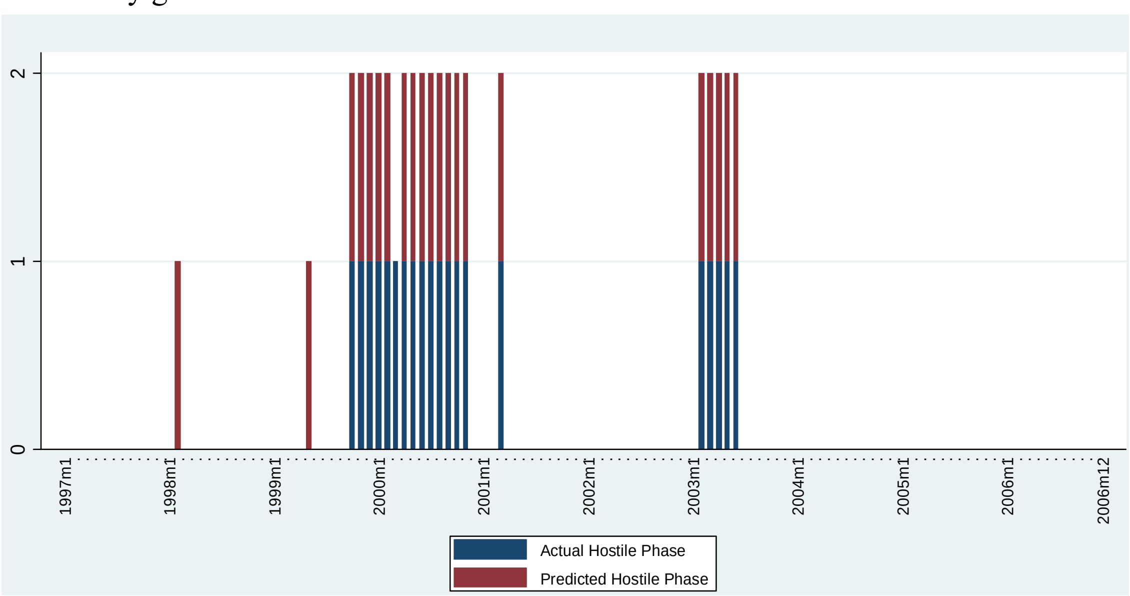


Figure 16: MILF In-Sample Predicted Values over Time

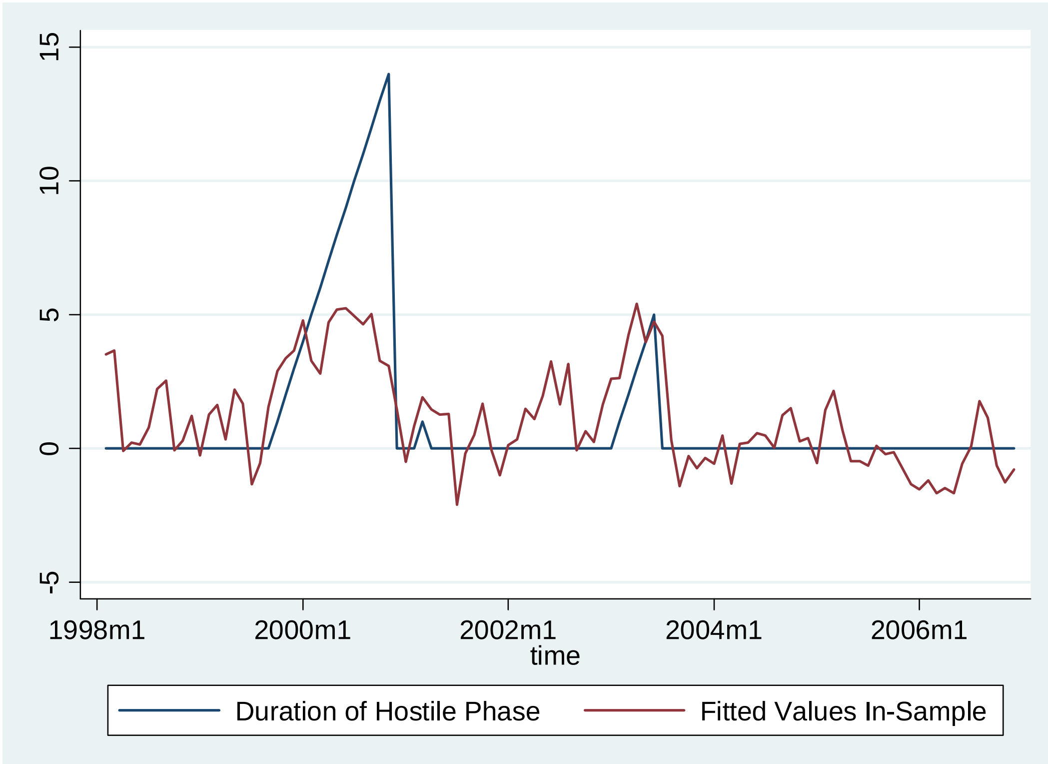


Figure 17: MILF Duration Model In-Sample Predicted Values

Figure 18 depicts the negative binomial model predicted values against the frequency of actual violent events carried out by the MILF in each month. The negative binomial model is also an excellent fitting model. In fact the predicted values and actual values correlate at .68.
Figure 19 depicts our actual hostile phase values against our model predicted hostile phase observations with the second phase being forecast out-of-sample. Our model is able to capture the second phase in the early part of 2003 without difficulty. It predicts all four phase values with one false positive at the end of the series. Overall, the model performs well when forecasting sustained hostile campaigns by the MILF out-of-sample.

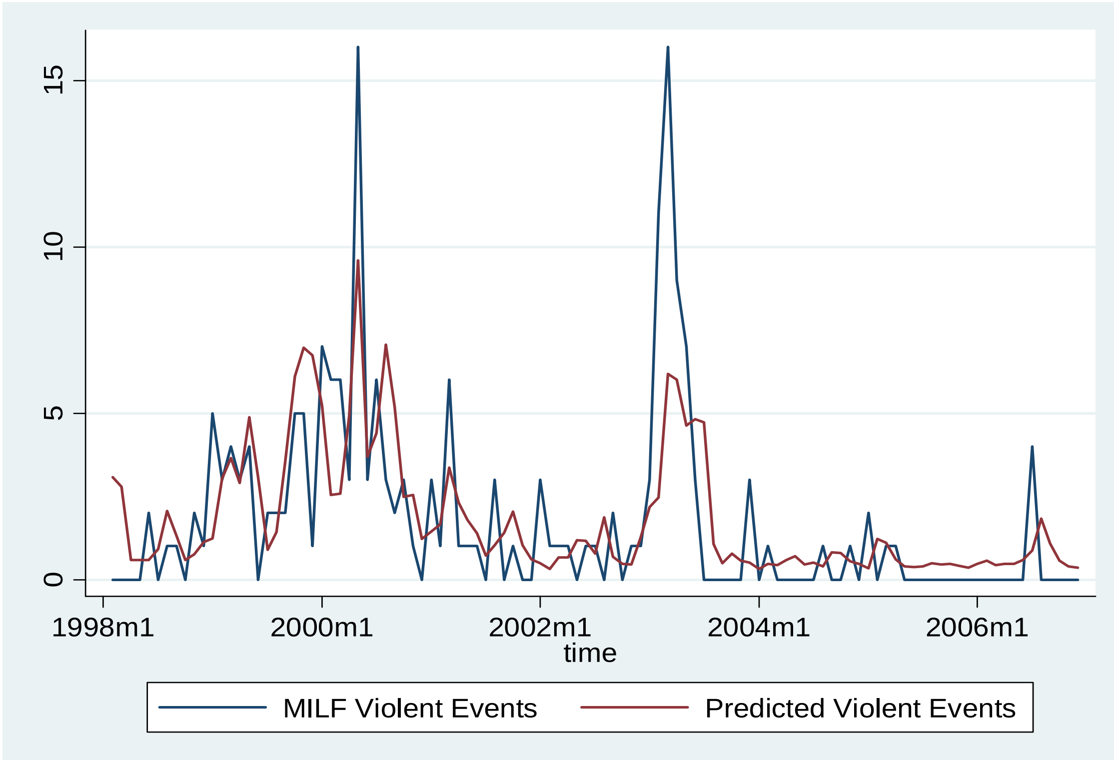


Figure 18: Negative Binomial In-Sample Predicted Values for MILF

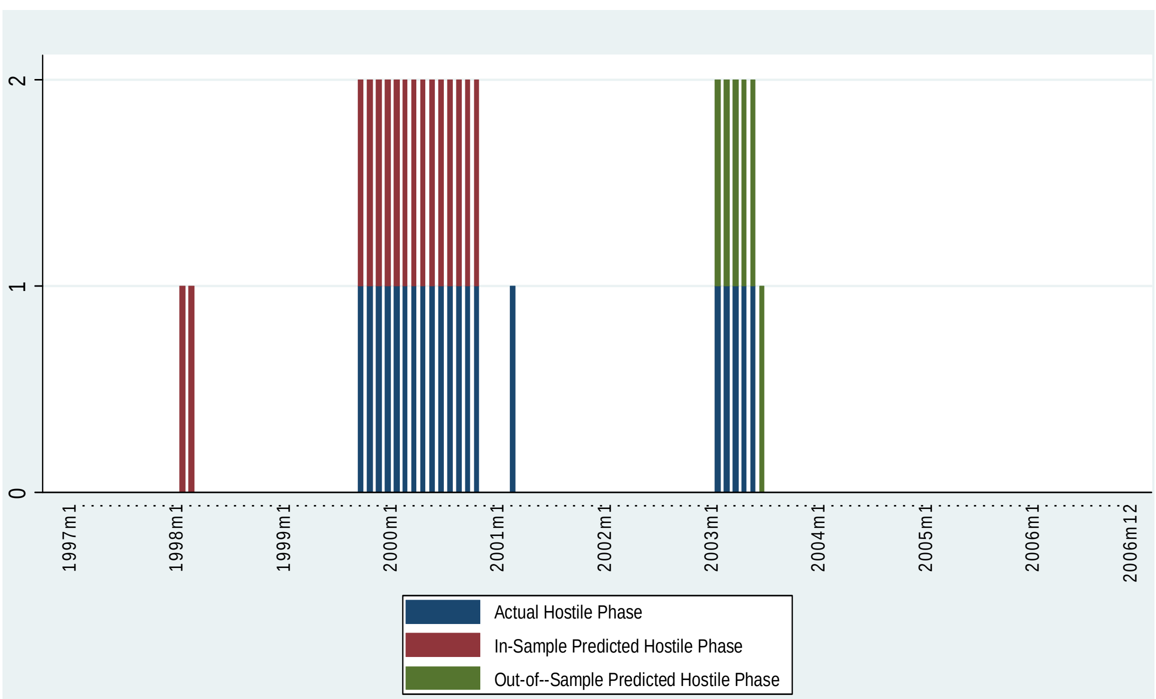


Figure 19: MILF Logit Model Out-of-Sample Forecast

Figures 20 and 21depict the out-of-sample duration forecasts. Figure 20 shows the raw forecast while Figure 21 smoothes out the forecast by taking a moving average across the estimates. Both figures show the model's ability to track well the duration of the major sustained campaigns of violence.

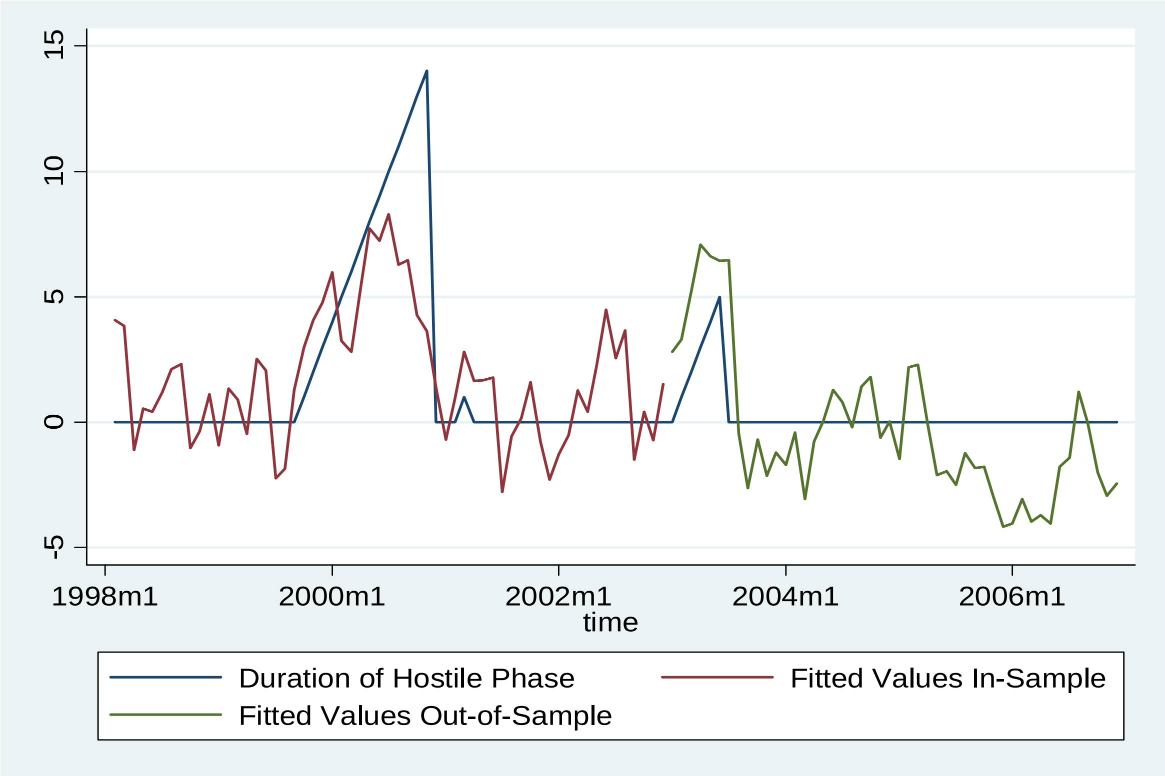


Figure 20: MILF Out-of-Sample Duration Model Forecast

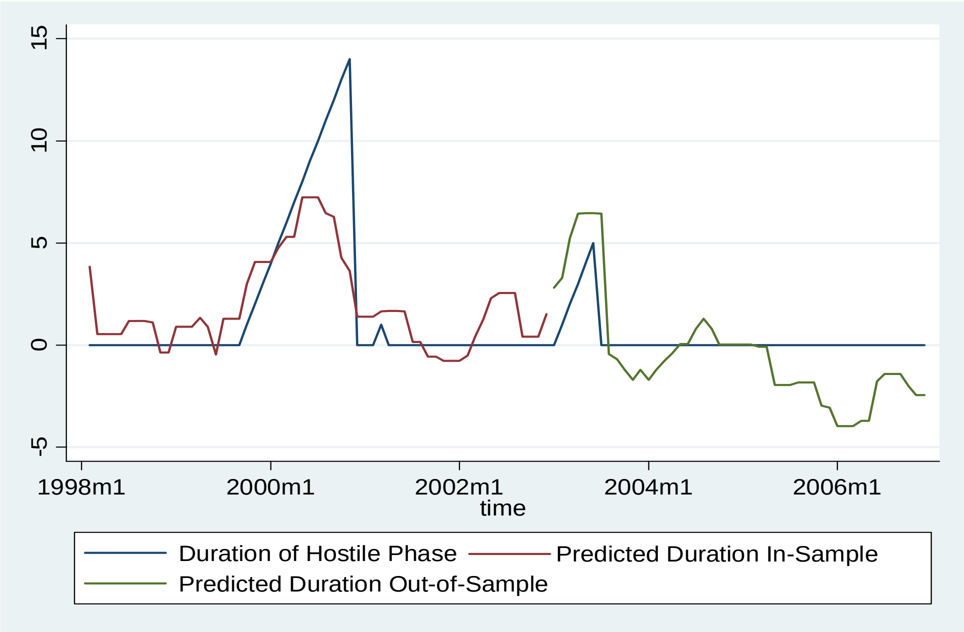


Figure 21: Out-of-Sample Duration Model Smoothed Forecast

Overall, the MILF model fits the hostile phase, campaign duration, and frequency of hostile events data well. All three dependent variables can be explained and forecast using this model. The model reveals little error in its ability to track these data well.

4.2.3 Bangladesh Chhatra League (BCL)

In addition to modeling separatist and insurgent groups' behavior, we also took on the challenge of modeling a student wing of a political party in Bangladesh, the BCL. While the BCL is historically credited with a tradition of leading national pro-democratic movements, members of the group more recently have engaged in terrorism and extortion. The BCL is an arm of Awami League who is in heated political competition with the BNP. Figure 22 reveals that the BCL engages in sustained violent activities during our period of analysis 4 times – early 2001, prior to and through the election of 2001, mid-2003, and late 2004 through 2006.

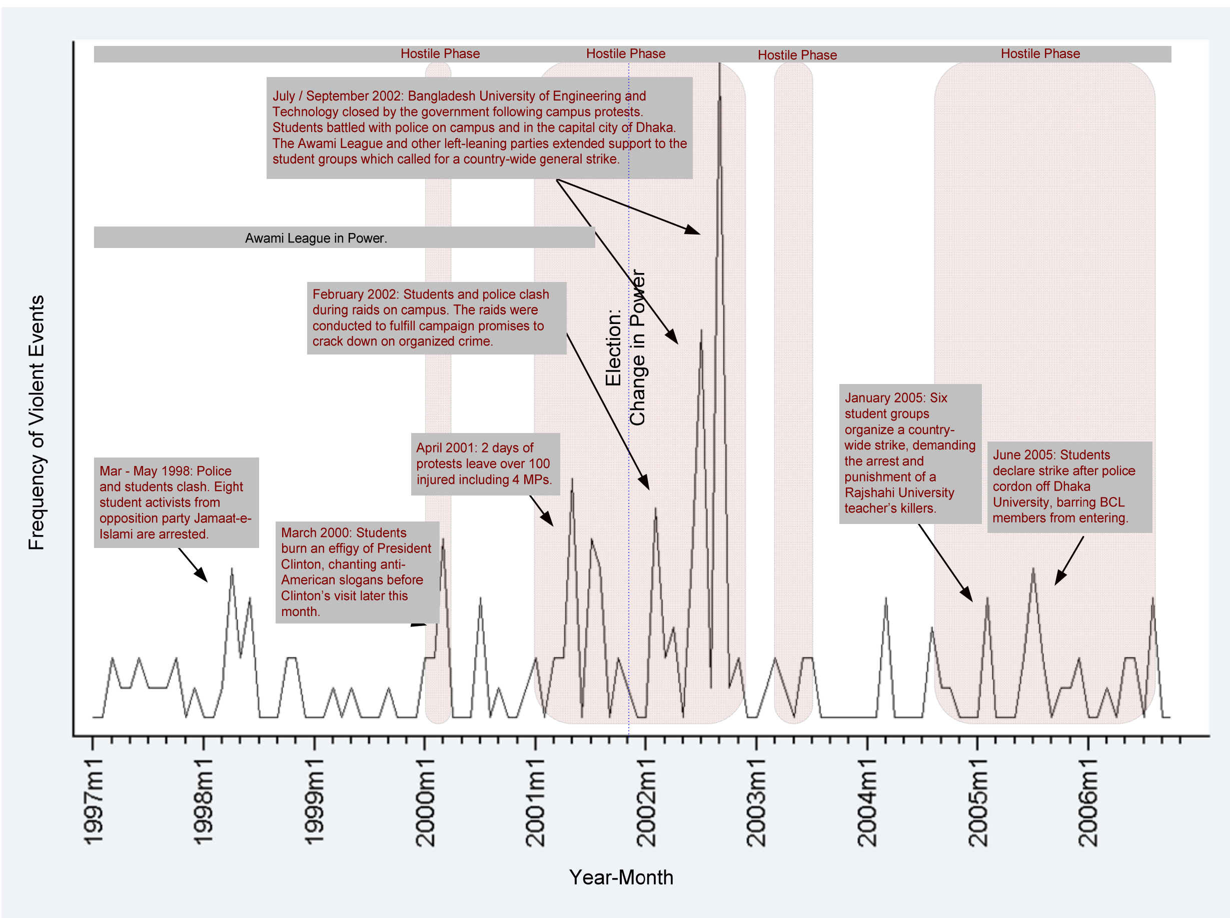


Figure 22: BCL Violent Phases

Given that BCL is closely intertwined with the Awami League who is in direct competition with the BNP, we needed to include measures of Awami-BNP interactions as well as government-BCL interactions. Moreover, the government in power changes during our time period in late 2001. So we include a variable denoting such change in our model. In a sense the BNP-Awami

interactions serve as the "competing group" interactions with the government in our model. Moreover, the BNP was charged with many human rights abuses when it took office in 2001 so we have included the Political Terror Scale (PTS) in our models which is a widely used 5-point scale of annual human rights abuses. The indicator is coded using US State Department records.

Table 6 reports our model's results for BCL Hostile Phase Changes. Along with the measures described above, it contains information on FDI, consumer food prices, government repression, low-level student hostile activities short of violence and our societal sentiment measures towards the government and the dissidents.

Table 6: Model of BCL Violence

Independent Variable	*Coef.*	*Std. Err.*	*Sig*[a]
Food CPI	-0.15078	0.067759	**
FDI	8.523548	2.489605	***
Human Rights Abuses (Political Terror Scale) (lagged 1 year)	-7.49549	2.333135	***
BNP Hostility towards Awami (lagged 1 month)	0.39829	0.093088	***
Awami Hostility towards BNP (lagged 1 month)	-0.467823	0.115998	***
BNP Hostility towards Awami (lagged 2 months)	0.27809	0.106504	***
Awami Hostility towards BNP (lagged 2 months)	-0.080537	0.04177	**
Student Low Level Hostile Actions (lagged 1 month)	0.776383	0.358643	**
Government Hostile Actions towards BCL	-0.060805	0.0651	
Government Hostile Actions towards BCL^2	0.001233	0.000424	***
Societal Sentiment towards the Government (lagged 1 month)	-0.76366	0.227437	***
Societal Sentiment towards the Dissidents (lagged 1 month)	0.32013	0.121217	***
Change of Power (Awami to BNP)	8.138626	2.712266	***
Constant	33.71437	11.26455	***
Wald Chi-Square	50.94	_	***
N	108	_	_
Pseudo R^2	0.69	_	_

[a] *=.10, **=.05, ***=.01 significance level – one-tailed tests.

All but one of the model's variables are statistically significant indicating that they are important to explaining and forecasting BCL behavior. The main findings we want to concentrate on include the interactions between the Awami League, BNP, the government in power and the students. To begin, as one may expect Awami hostility towards BNP decreases BCL violence as Awami is taking the lead. Whereas, BNP violence directed toward the Awami League increases violence by BCL. This is the case for both lags on both variables. As BNP ramps up the violence, the student league also ramps up its violence. While low level government repression does not yield an impact on BCL violence, high level repressive activities yields an increase in BCL violence. However, human rights abuses have a negative effect on BCL violence. The change of power also yields an increase in BCL violence. The time leading up to the election is the beginning of one of BCL's violent campaigns and this is sustained and ramped up following

the election of BNP to power. Finally, as with our other models, support for the government yields a decrease in BCL violence while support for dissidents yields an increase in BCL violence. We tried interacting many of the government repression variables and the Awami and BCL variables with change in power and found some interesting things. Repression by Awami and by the BNP affected BCL activities dissimilarly. However, such complicated interactions did not improve the overall fit of the model or the model's ability to forecast. As a result, we defaulted to the more parsimonious model. Much of the variation in our model is explained by the Awami-BNP directed dyadic hostility variables. As a result, we think, the interactions we created just muddied the relationships. The BCL clearly pays attention to Awami-BNP interactions and acts accordingly.

As we stated, our parsimonious model is a good fit for these data. Figure 23 shows that the ROC covers over 96% of the area under the curve. Table 7 further illustrates that our model correctly classifies about 90% of the observations correctly with a high degree of sensitivity (91%) and specificity (88%). Overall the model misclassifies 10 of 95 observations.

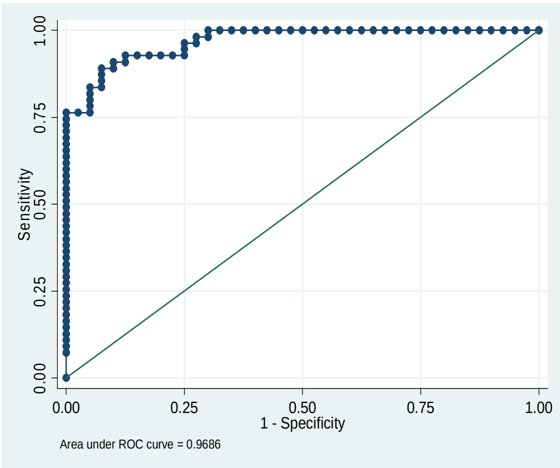


Figure 23: BCL ROC Curve

Table 7: BCL Classification Results

Classified	True D	True ~D	Total
+	50	5	55
-	5	35	40
Total	55	40	95

Classified + if predicted Pr(D) >= .495
True D defined as HPstudent4 != 0

Sensitivity	Pr(+| D)	90.91%
Specificity	Pr(-|~D)	87.50%
Positive predictive value	Pr(D| +)	90.91%
Negative predictive value	Pr(~D| -)	87.50%
False + rate for true ~D	Pr(+|~D)	12.50%
False - rate for true D	Pr(-| D)	9.09%
False + rate for classified +	Pr(~D| +)	9.09%
False - rate for classified -	Pr(D| -)	12.50%
Correctly classified		89.47%

Figure 24 further illustrates the model's capabilities in fitting the trends in the data well. It clearly picks up the sustained campaigns of violence after 2000. The model is very good at explaining the onset of violent campaigns after 2000 and fairly good at explaining their cessation.

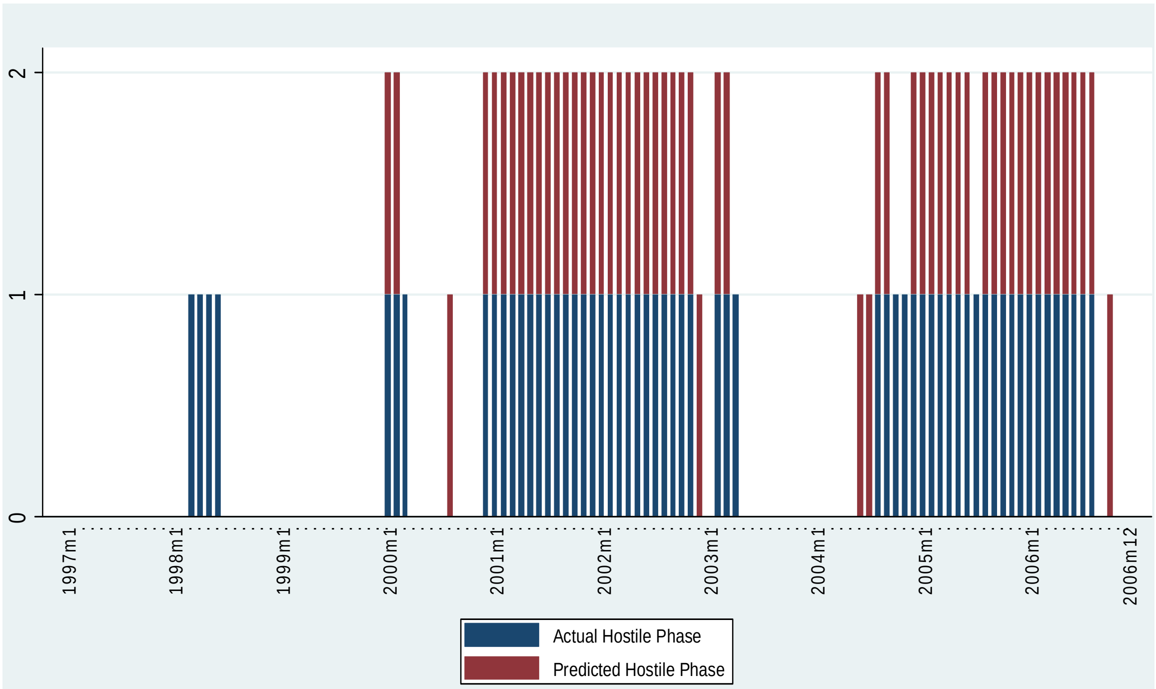


Figure 24: BCL In-Sample Predicted Values over Time

Figure 25 depicts how well our model fits the duration data on BCL campaigns. Clearly one observes that the model does an excellent job at tracking the duration of violent campaigns overtime – especially the two major campaigns.

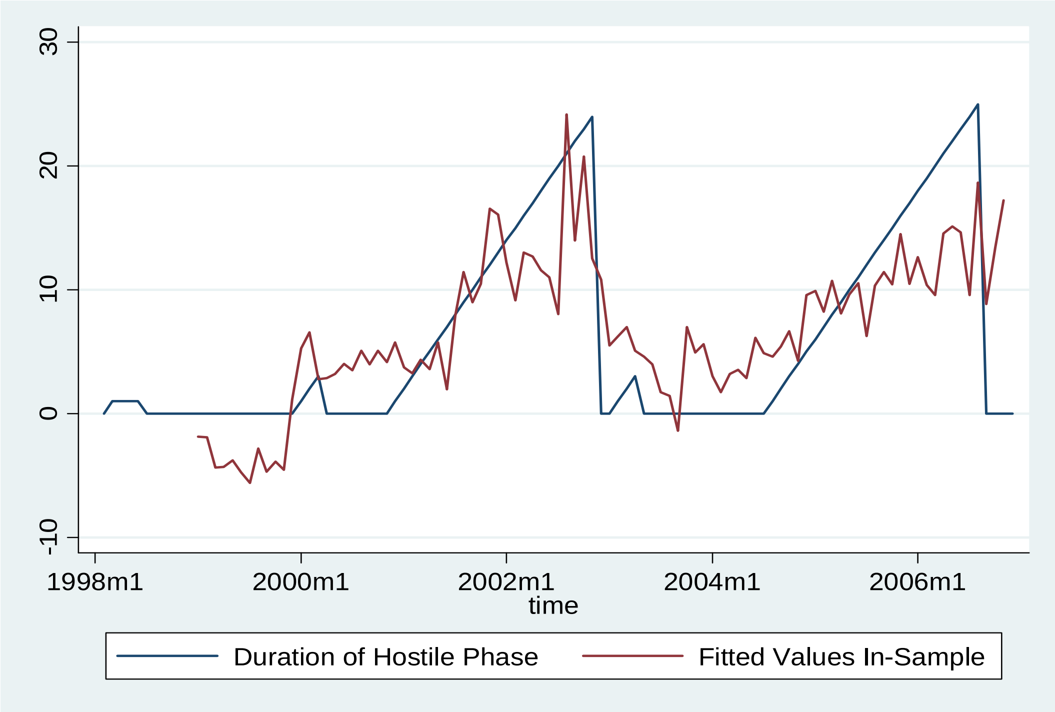


Figure 25: BCL Duration Model In-Sample Predicted Values

Figure 26 reports how well the predicted values from the negative binomial model trend with the actual frequency of BCL violent events every month. While the predicted and actual values only correlate at .52, the predicted values reveal the overall trends of the actual series well.

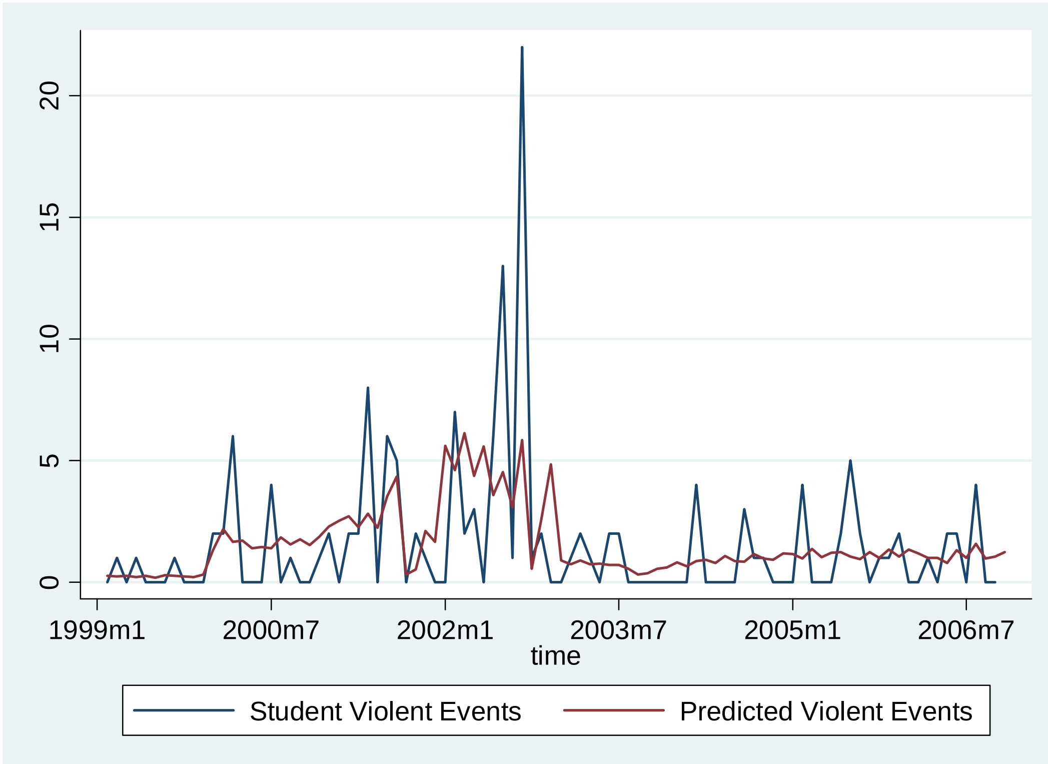


Figure 26: Negative Binomial In-Sample Predicted Values for BCL

Now we turn to our out-of-sample forecasts. Figure 27 shows that our out-of-sample forecast of the last BCL hostile phase is fairly accurate. While the forecast does not miss any true positives it does produce a few false positives prior to the campaign and following the campaign. These false positives indicate the high probability of violent activity, which in this case materializes and can be valuable to the analyst who must anticipate group violence.

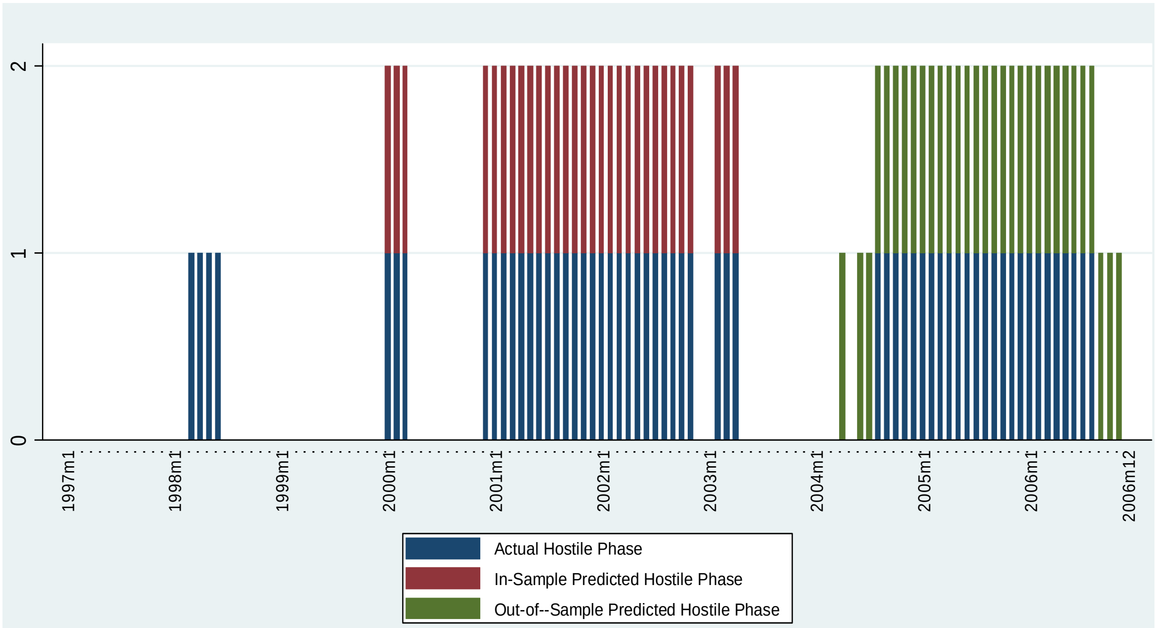


Figure 27: BCL Logit Model Out-of-Sample Forecast

Figure 28 shows that while our in-sample predictions for the duration of BCL violent phases are excellent; our out-of sample predictions may not seem as accurate. The out-of sample forecast does not trend up and back down like it should in 2005 and 2006, but the overall level of the series is higher than the mean during this time period and the overall rise and fall of the mean of the series during this time period demarcates the beginning and ending of the BCL violent campaign. Thus, while at first glance, the model does not seem to do well forecasting the duration of BCL violent campaigns out-of-sample, a second look reveals it is not so bad.

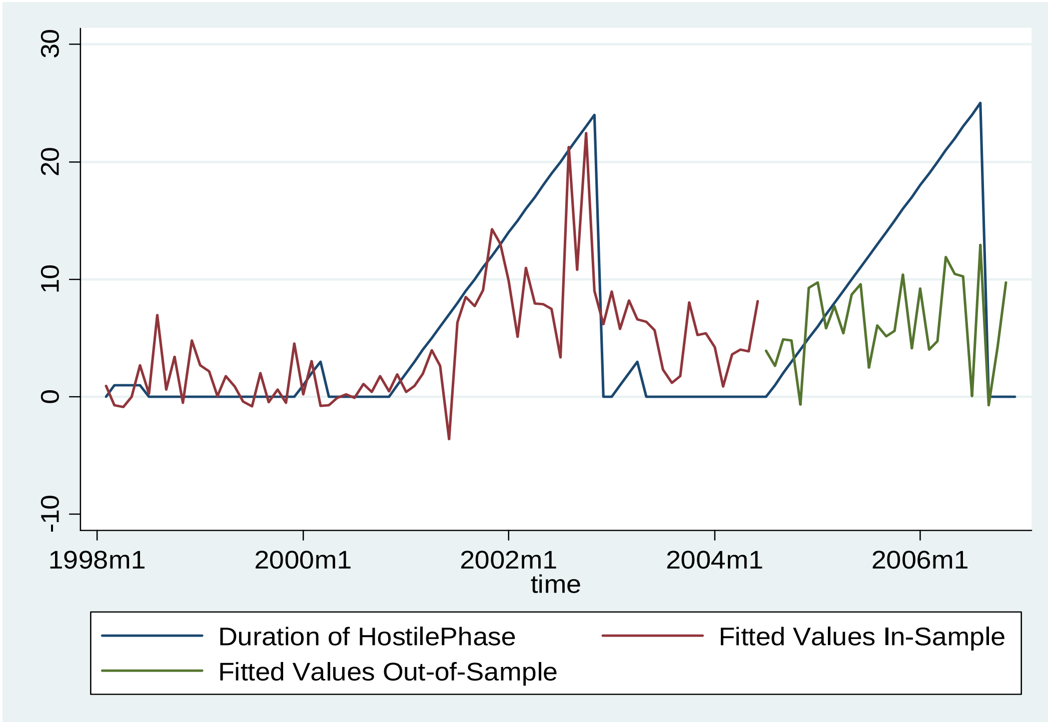


Figure 28: BCL Out-of-Sample Duration Model Forecast

Overall, our model of BCL violent campaigns and violent activities across all three dependent variables performs well. It is able to pick up the onset and cessation of sustained violent campaigns both in and out-of-sample with high accuracy, sensitivity, and specificity.

4.2.4 People's War Group (PWG)

The PWG is a Maoist/communist group established in the Southern Indian State of Andhra Pradesh wishing to establish a "people's government" through peasant insurrection. The PWG exhibits five major campaigns during our period of study which are depicted in Figure 29. The last one in 2004-early 2006 is the longest and was partially carried out in tandem with the Maoist Communist Centre (MCC), another armed group with similar goals.

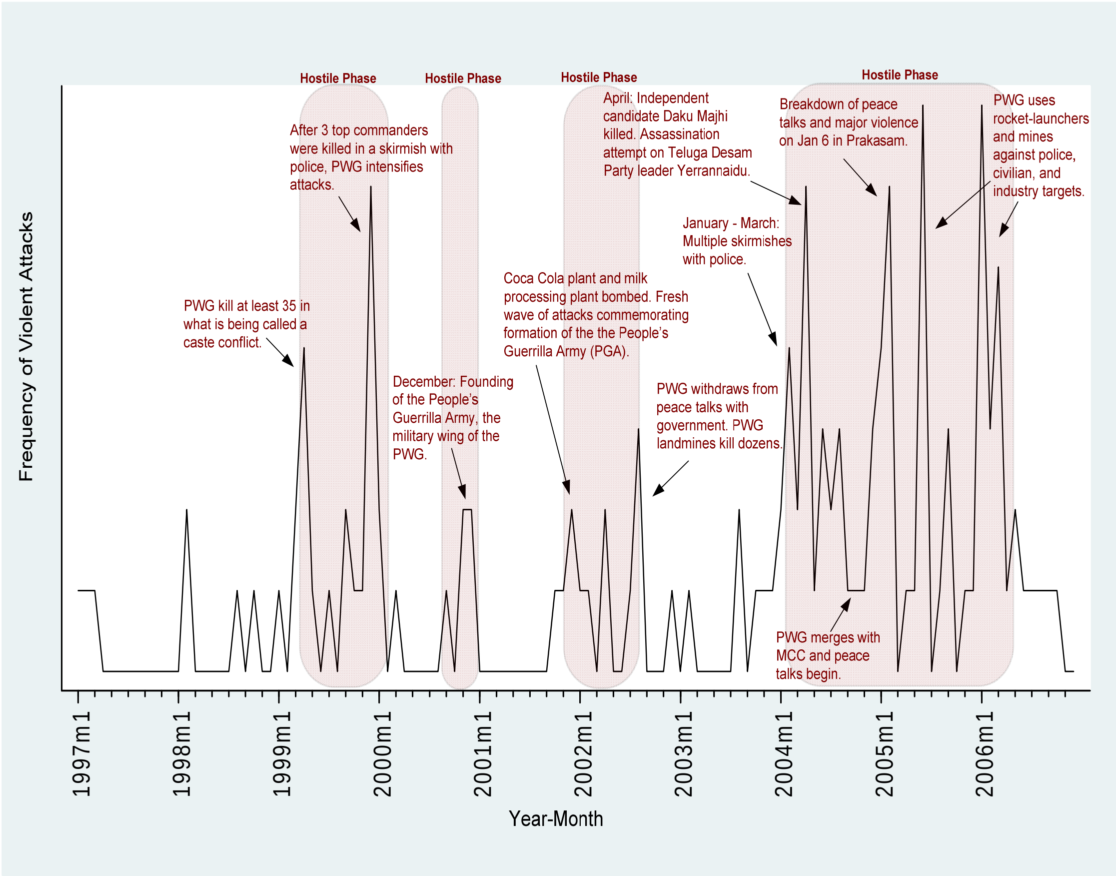


Figure 29: PWG Hostile Phases

Our model combines information on the interactions among the government and other separatists groups not including PWG or MCC as well as MCC specifically. It also includes our other standard repression and sentiment variables. The PWG seemed to key off information not just in the most recent past but a couple months prior. Thus, most of the variables are lagged two months.

Table 8 reports our results. The PWG does key off of other groups' violent activities. The second lag of MCC violence and the first lag of non-PWG and MCC groups' violent activities yield positive and statistically significant effects on the probability that PWG engages in a sustained campaign of violence. While low level government actions towards other groups do not yield any significant impact on PWG behavior, high-level repressive acts (squared terms) towards other groups does yield positive effects. Yet, low and high levels of repression directed towards PWG yields lower probabilities of sustained violent activities. Other interesting results are the findings for sentiment. Support for the government yields increases in violence, while dissident support yields slight negative effects on PWG violence. As the PWG garners more support, it is less likely to sustain large campaigns of violence.

Table 8: Model Results for PWG Violent Phases

Independent Variable	*Coef.*	*Std. Err.*	*Sig*[a]
MCC Violent Attacks (lagged 1 month)	0.26845	.76866	
MCC Violent Attacks (lagged 2 months)	1.26439	.78687	**
Government Repression towards Other Separatist Groups	-0.00061	0.00544	
Government Repression towards Other Separatist Groups ^{2}	6.21E-06	3.89E-06	**
Government Repression towards Other Separatist Groups	.002513	.00531	
Government Repression towards Other Separatist Groups ^{2}	5.52E-06	2.35E-06	***
Other Separatist Groups' Violent Attacks	-0.38347	0.02791	*
Other Separatist Groups' Low-Level Hostile Actions	0.106	0.0619	**
Government Repression towards PWG (lagged 1 month)	.10563	0.07269	*
Government Repression towards PWG (lagged 2months)	-0.08908	0.037358	***
Societal Sentiment towards the Government (lagged 1 month)	0.18710	0.12704	*
Societal Sentiment towards the Government (lagged 2 months)	0.18935	0.10556	**
Societal Sentiment towards the Dissidents (lagged 1 month)	0.00062	0.10048	
Societal Sentiment towards the Dissidents (lagged 2 months)	-0.1176	0.09053	*
Constant	-6.6403	2.337	***
Wald Chi-Square	30.93	_	***
N	117	_	_
Pseudo R^2	0.61	_	_

[a] *=.10, **=.05, ***=.01 significance level – one-tailed tests.

Table 9 shows that our model fits the data well by classifying almost 92% of the observations correctly. Only 10 of 117 observations were misclassified resulting in sensitivity levels of 92% and specificity levels of almost 91%. Figure 30 shows that the model covers almost 97% of the area under the curve. These statistics suggest the model is an excellent fit for the data.

Table 9: PWG Classification Results

Classified	True D	True ~D	Total
+	59	5	64
-	5	48	53
Total	64	53	117

Classified + if predicted Pr(D) >= .495
True D defined as HPPWG != 0

Sensitivity	Pr(+| D)	92.19%
Specificity	Pr(-|~D)	90.57%
Positive predictive value	Pr(D| +)	92.19%
Negative predictive value	Pr(~D| -)	90.57%
False + rate for true ~D	Pr(+|~D)	9.43%
False - rate for true D	Pr(-| D)	7.81%
False + rate for classified +	Pr(~D| +)	7.81%
False - rate for classified -	Pr(D| -)	9.43%
Correctly classified		91.45%

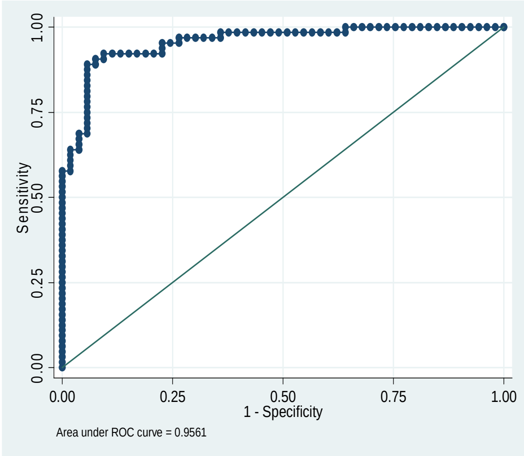


Figure 30: PWG ROC Curve

The model explains both violent phases (Figure 31) and the duration of violent phases (Figure 32) very well. Figure 31 shows that the model does well temporally in terms of predicting the phases across time. Figure 31 shows the model does well at modeling the onset and cessation of violent campaigns. Figure 32 shows that the model predicted smoothed values (i.e., by taking the moving average) fit the duration data well. They tend to move up and down with the actual data series as the phases begin, continue for a bit, and end.

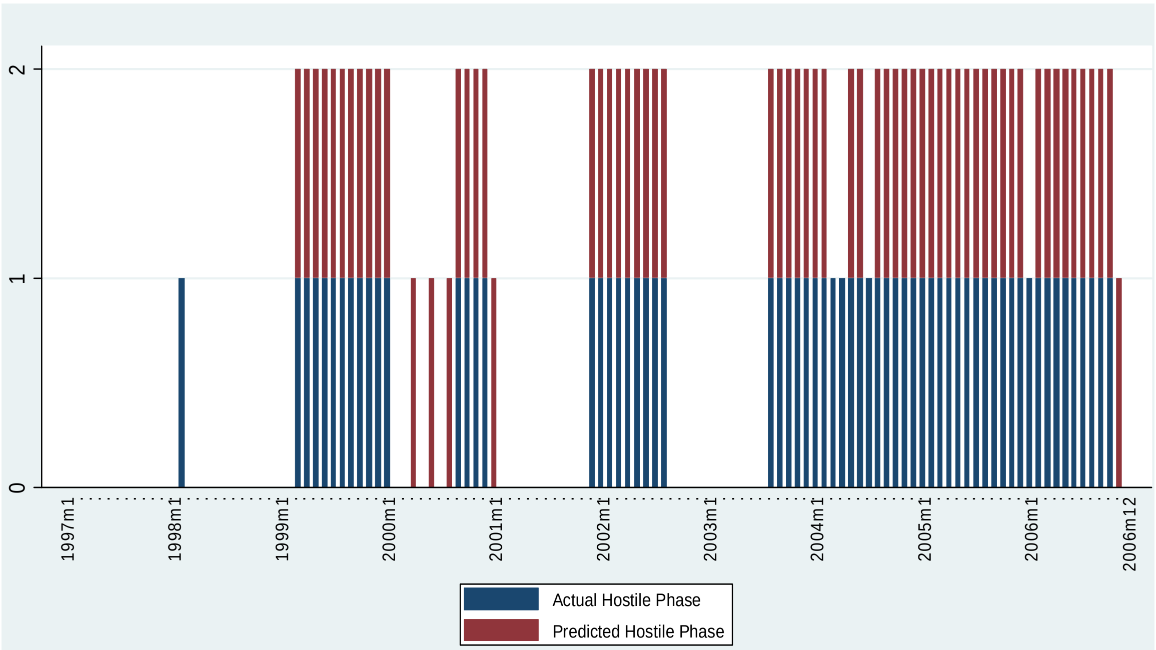


Figure 31: PWG In-Sample Predicted Values over Time

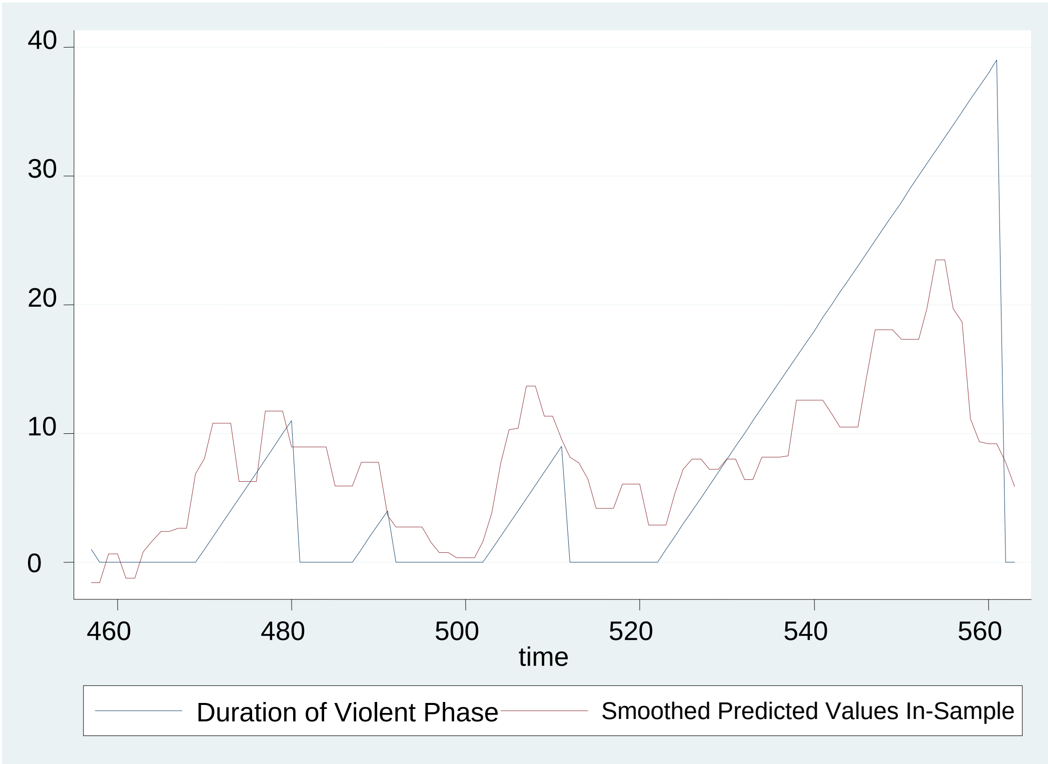


Figure 32: PWG Duration Model In-Sample Predicted Values

Figure 33 shows the results of our negative binomial specification. Like the other models, the count model predicted values closely mirroring the average trends in the actual series of violent events carried out by the PWG.

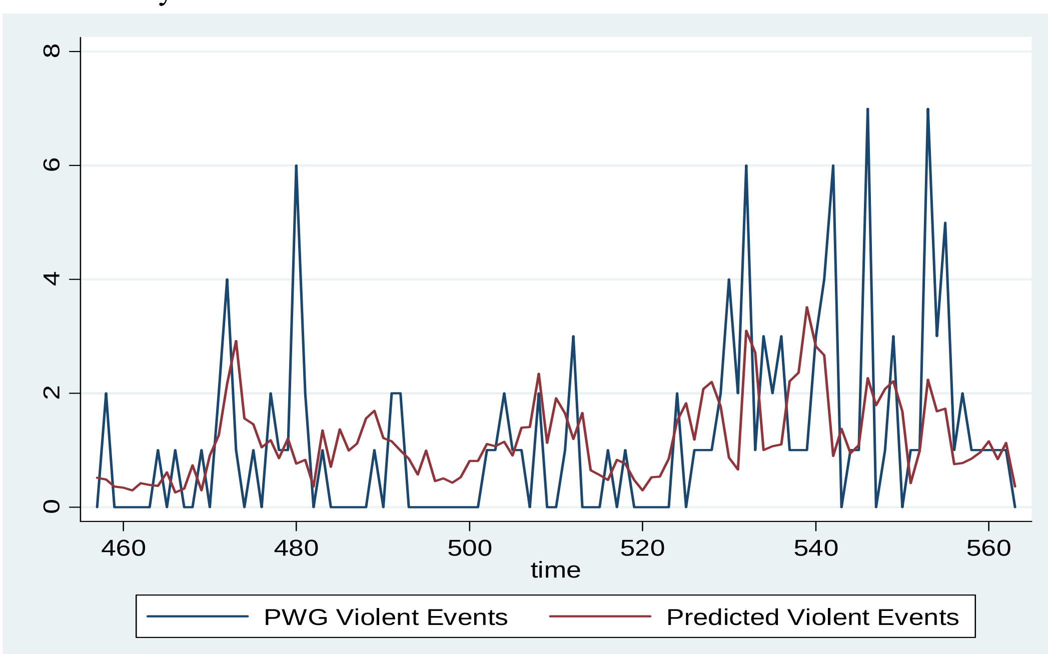


Figure 33: Negative Binomial In-Sample Predicted Values for PWG

Finally, we examine our model's ability to forecast out-of-sample. Figure 34 shows our model's predicted values for hostile phases. Figure 34 reveals that our forecast misses 10 out of 47 observations. While we'd certainly like fewer false negatives, the model does well at anticipating the beginning and ending of the out-of-sample phase. Moreover, there is much ebb and flow in violence during that final sustained campaign of violence in our period of study. Figure 35 shows the in and out-of-sample forecast for our duration model. While the in-sample predictions look great, the out-of-sample is a bit weak. That said, it still curves upward and back down in concert with the length of the PWG campaign.

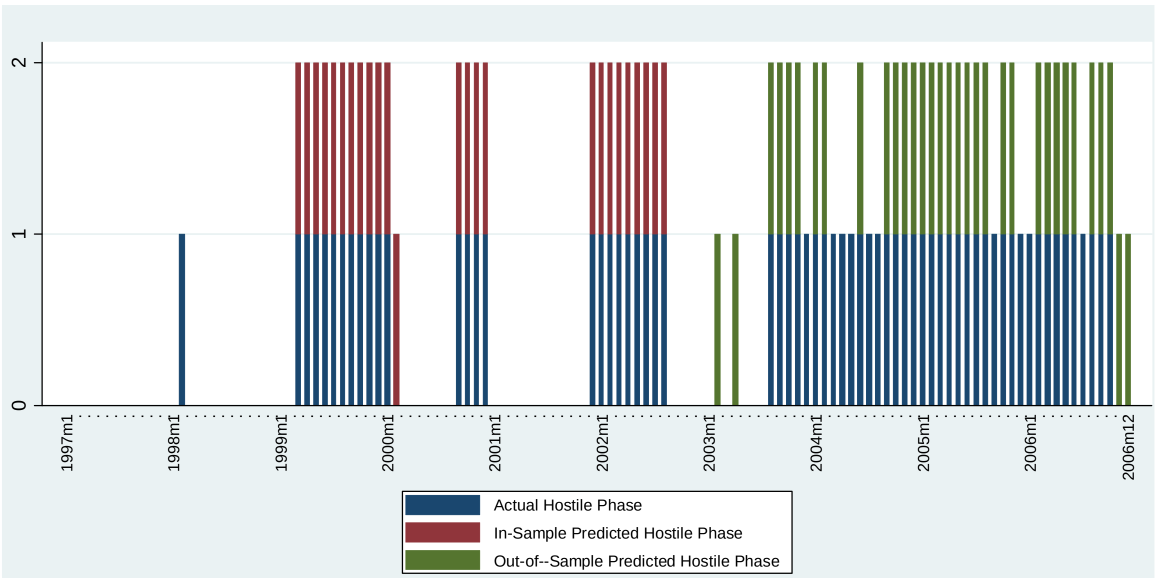


Figure 34: PWG Logit Model Out-of-Sample Forecast

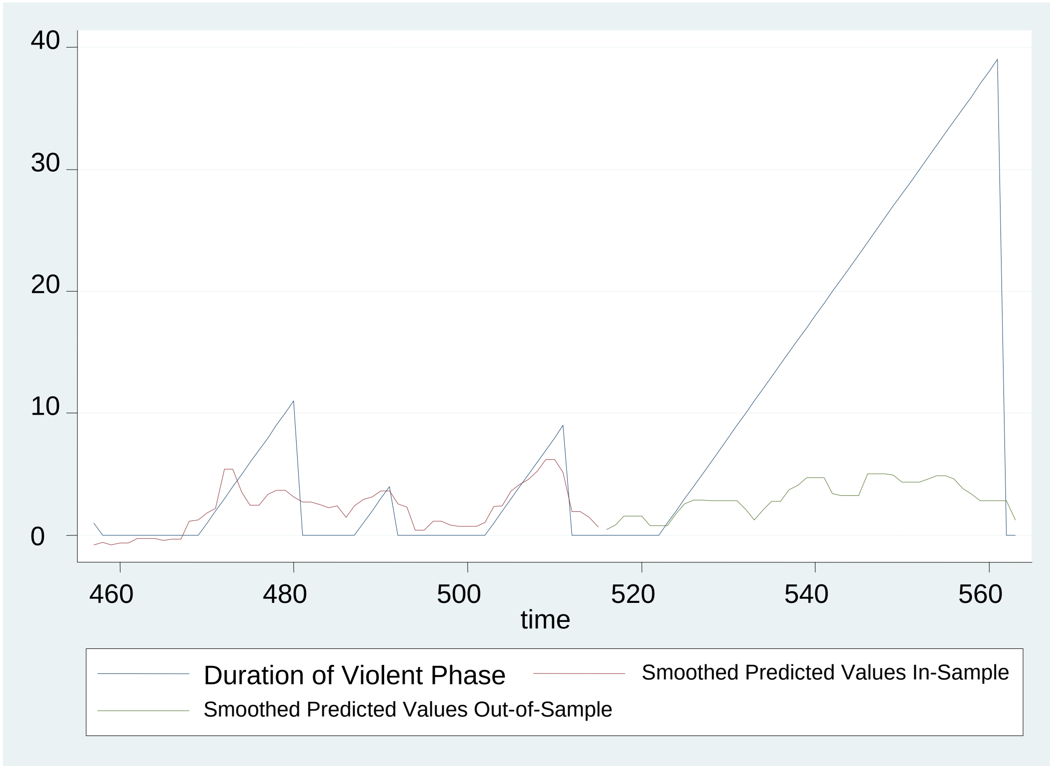


Figure 35: PWG Out-of Sample Duration Model Smoothed Forecast

Overall, the PWG model is the weakest of the bunch in terms of its out-of-sample forecasting abilities but it still exceeds most accepted metrics for accuracy.

4.2.5 Free Papua Movement or Organisasi Papua Merdeka (OPM)

The OPM is a separatist organization wishing to establish an independent state across the regions of Papua and West Papua of Indonesia. During our period of study, OPM engaged in four major sustained campaigns of violence. Each of these violent phases is depicted in Figure 36.

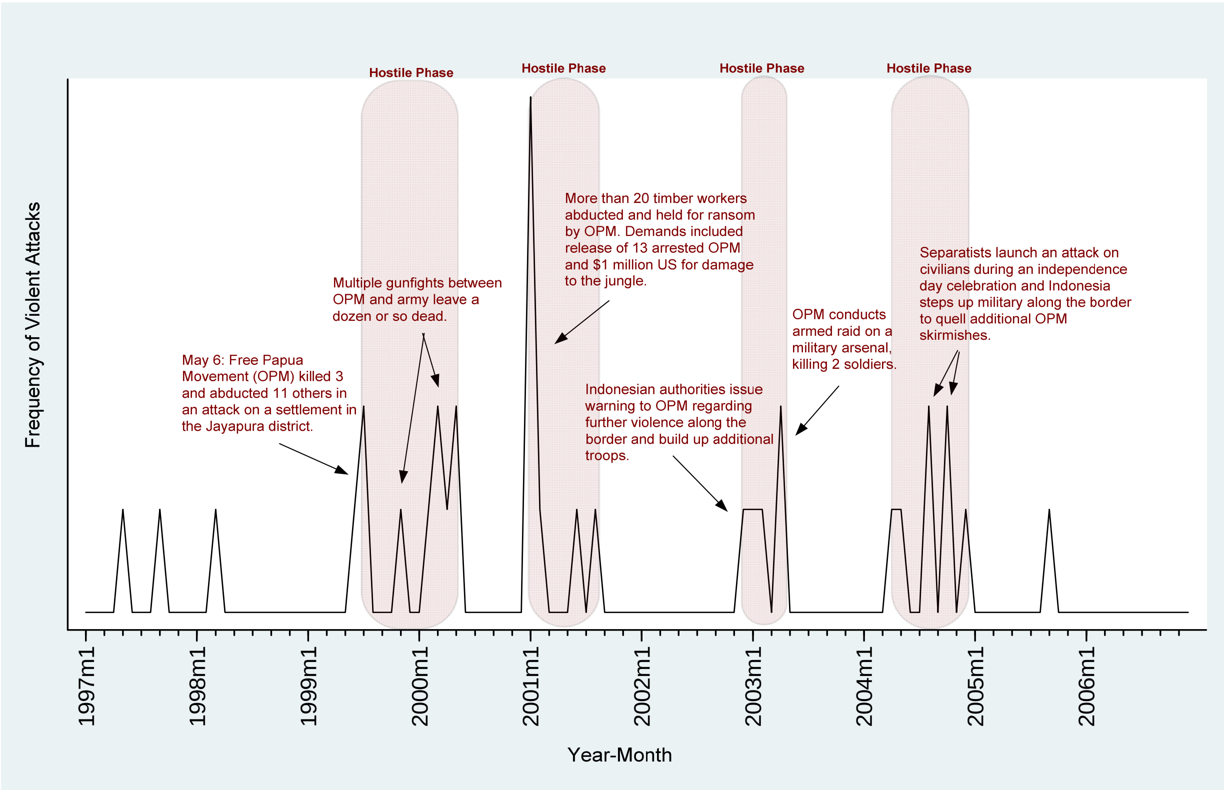


Figure 36: OPM Violent Phases

Our model includes the usual suspects that our prior models have included but the OPM tactical decisions and campaigns seem to exhibit more long term memory than our other groups. That is, while we include our repression, sentiment, and competing groups actions in our model, the best fit for sustained violent campaigns by the OPM were obtained by lagging each of these variables two and or three months.

Table 10 reports our results. The OPM clearly monitor the interactions of the state and other separatist groups – especially the Free Aceh Movement (GAM) another major group fighting for their own independent state in another part of the country. We created specific indicators of GAM violence and government repression towards GAM and included those in our model. It appears that GAM attacks in the recent past yield a higher probability that OPM sustains violent attacks in the current month, but GAM attacks in the more distant past yield a lower likelihood that OPM sustained violent attacks in the current month. State repressive activities towards GAM in the recent and more distant past (1 to 3 months) yield inverted-U effects on the probability that OPM engages in violent campaigns. That is, moderate levels of state repression directed towards GAM yield a higher propensity that a violent campaign will be carried out by OPM. Oddly enough, OPM only responded to state repressive actions a couple months back and the relationship was linear as opposed to curvilinear. That is, the harsher the actions the more likely OPM was to engage in sustained violent activities. We also created an indicator of all other separatist groups violent activities in India. This indicator did not include attacks by GAM or by

OPM but by other separatist groups in Indonesia. Other groups' actions in the more recent past sparked sustained violent activities by OPM.

Table 10: Logit Model Results for OPM Violent Phases

Independent Variable	*Coef.*	*Std. Err.*	*Sig*[a]
All Other Separatist Groups' Violent Attacks (lagged 1 month)	0.963046	0.268521	***
All Other Separatist Groups' Violent Attacks (lagged 2 month)	1.402275	0.375168	
GAM Violent Attacks (lagged 1 month)	0.821248	0.599109	*
GAM Violent Attacks (lagged 2 month)	-1.00655	0.434475	***
GAM Violent Attacks (lagged 3 month)	-0.27474	0.38079	
Government Hostility towards GAM (lagged 1 month)	0.03483	0.084207	
Government Hostility towards GAM (lagged 2months)	0.16448	0.06029	***
Government Hostility towards GAM (lagged 3 month)	0.2664	0.071184	***
Government Hostility towards GAM ^{2} (lagged 1 month)	-0.00339	0.001609	**
Government Hostility towards GAM ^{2} (lagged 1 month)	-0.0028	0.000801	***
Government Hostility towards GAM ^{2} (lagged 1 month)	-0.00254	0.000674	***
Government Hostility towards OPM (lagged 1 month)	0.1279	0.181284	
Government Hostility towards OPM (lagged 2months)	0.257003	0.127504	**
Government Hostility towards OPM (lagged 3 month)	0.029619	0.104144	
Societal Sentiment towards the Government (lagged 1 month)	-0.57207	0.213535	***
Societal Sentiment towards the Government (lagged 2 month)	-0.47582	0.132664	***
Societal Sentiment towards the Government (lagged 3 month)	-0.12064	0.215688	
Societal Sentiment towards the Dissidents (lagged 1 month)	-0.06664	0.186524	
Societal Sentiment towards the Dissidents (lagged 2 month)	-0.55665	0.267583	**
Societal Sentiment towards the Dissidents (lagged 3 month)	0.120639	0.34716	
Societal Sentiment towards the Dissidents^2 (lagged 1 month)	0.088712	0.038538	***
Societal Sentiment towards the Dissidents^2 (lagged 3 month)	-0.21325	0.079351	***
Constant	-9.2803	1.675068	***
Wald Chi-Square	50.43	_	***
N	117	_	_
Pseudo R^2	0.67	_	_

[a] *=.10, **=.05, ***=.01 significance level – one-tailed tests.

In terms of sentiment, we find that as support for the government increases, the probability that OPM engages in violent campaigns decreases. This is consistent with most of our other findings. We did uncover more nuanced findings for dissident support. Support for dissidents three months prior yielded slight curvilinear but overall negative effects on OPM violent campaigns in the current month. While support two months prior was still overall negative and the effect was more linear. However, when support for the dissidents was high in the most recent month, the probability increased that OPM would engage in a violent campaign. So while distant past support yielded lower probabilities of violent campaigns, high levels of dissident support in the

previous month yielded high probabilities that dissidents would engage in violent campaigns. While we did not further investigate this finding, we think that support may subside after campaigns of violence, after all the group terrorized citizens and as support increased as violence subsided, OPM would again engage in violence only to see support decrease again. We'd need to explore the two-way causation between support and actions in order to test our claim and that was not really the focus of our current project but provides a fruitful avenue for future work – the interplay and endogenous relationships between support and action.

That said, our current project focuses on explaining and forecasting OPM violent campaigns and our model succeeds at this task. The ROC depicted in Figure 37 curve contains almost 97% of the area under the curve. Table 11 shows that our model classifies almost 95% of the observations correctly while maintaining high levels of sensitivity (87%) and specificity (98%). Overall, the model misclassifies only 6 observations – four false negatives and 2 false positives. One can also see that temporally, our model does very well at classifying observations in correct temporal clusters. That is, it groups and picks up well on the campaigns and non-campaigns over time. Figures 38 and 39 plots the results from our duration model and one can see that the peaks in our estimates are centered within each of the hostile phases indicating that the model does a terrific job at explaining the onset and duration of OPM violent phases. Figures 40 and 41 illustrated the predicted versus actual values of our negative binomial model. Figure 41 smoothes out the estimates to better visualize how the model estimates the average peaks and valleys of the frequency of violent attacks by OPM over time. All three models together provide convincing evidence that our model can explain the variation in violent activities and campaigns carried out by the OPM during our period of study.

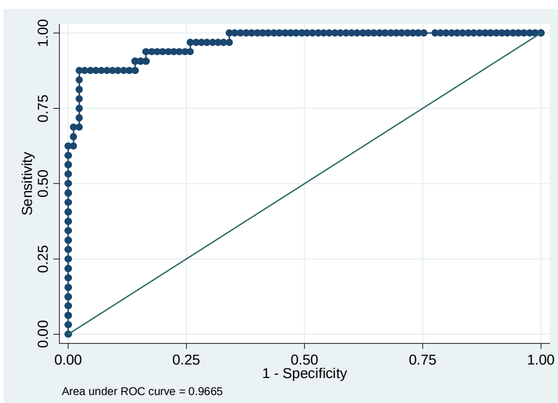


Figure 37: OPM ROC Curve

Table 11: OPM Classification Results

Classified	True D	True ~D	Total
+	28	2	30
-	4	83	87
Total	32	85	117

Classified + if predicted Pr(D) >= .5
True D defined as HPOPM != 0

Sensitivity	Pr(+| D)	87.50%
Specificity	Pr(-|~D)	97.65%
Positive predictive value	Pr(D| +)	93.33%
Negative predictive value	Pr(~D| -)	95.40%
False + rate for true ~D	Pr(+|~D)	2.35%
False - rate for true D	Pr(-| D)	12.50%
False + rate for classified +	Pr(~D| +)	6.67%
False - rate for classified -	Pr(D| -)	4.60%
Correctly classified		94.87%

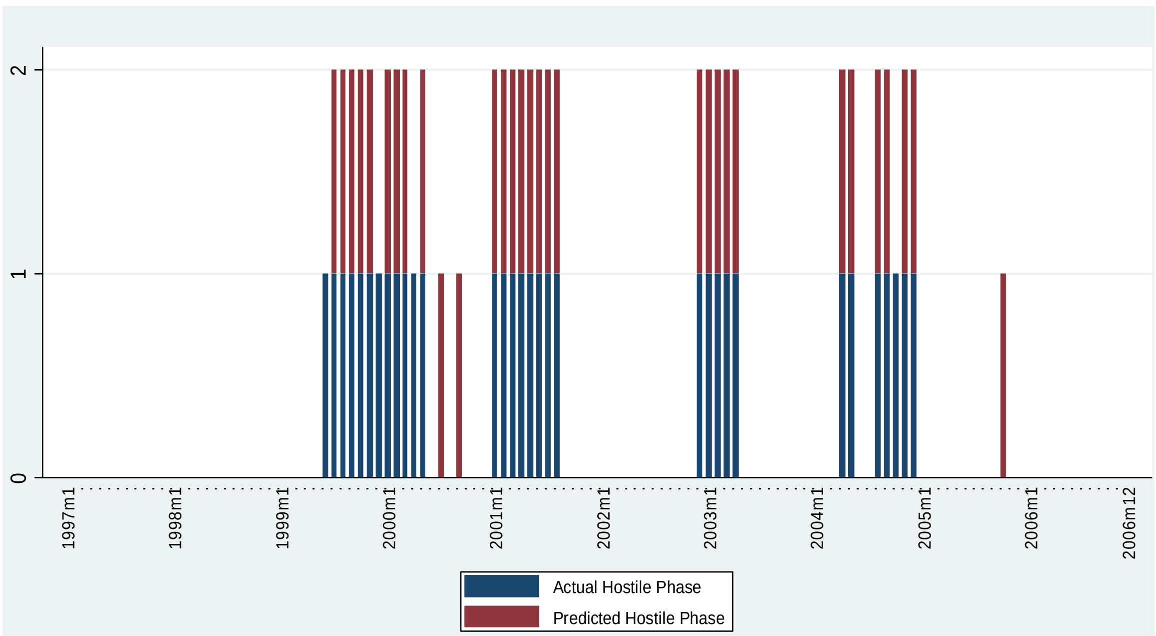


Figure 38: OPM In-Sample Predicted Values over Time

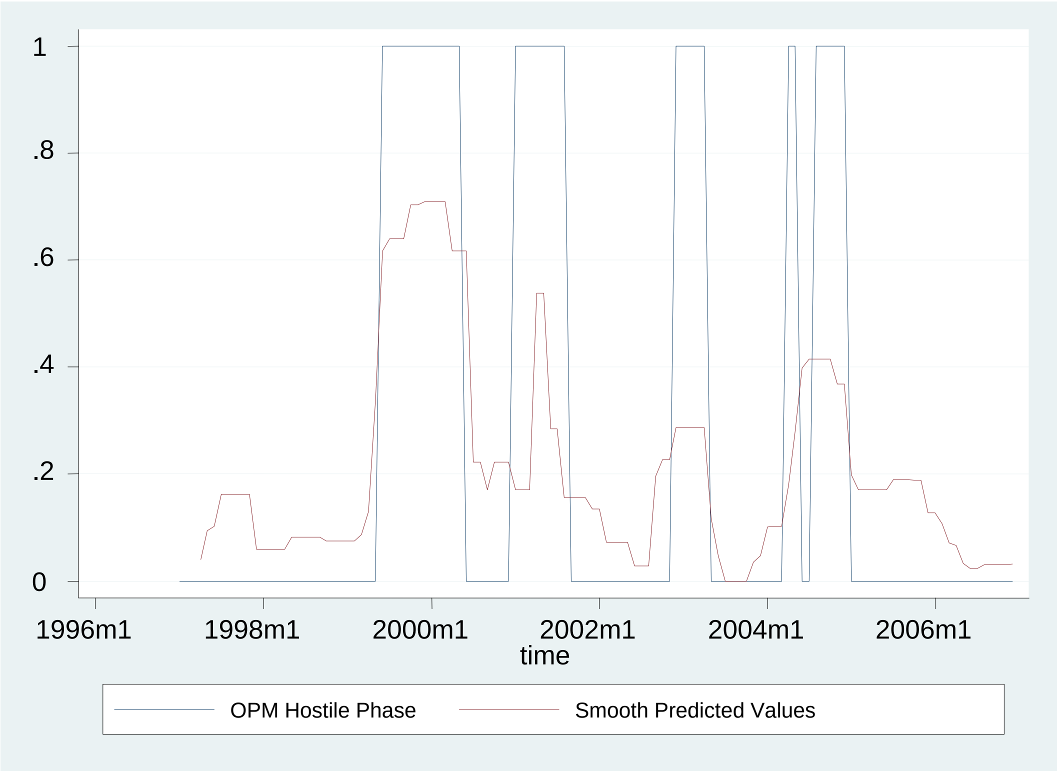


Figure 39: OPM Duration Model In-Sample Predicted Values (Smoothed)

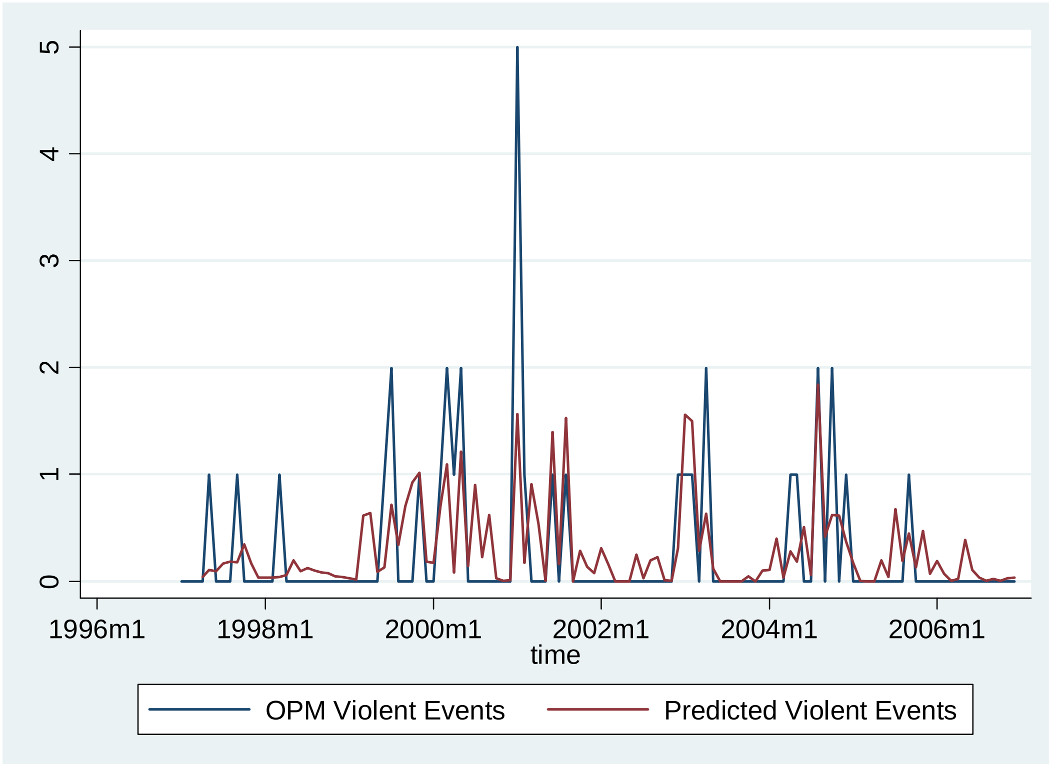


Figure 40: Negative Binomial In-Sample Predicted Values for OPM

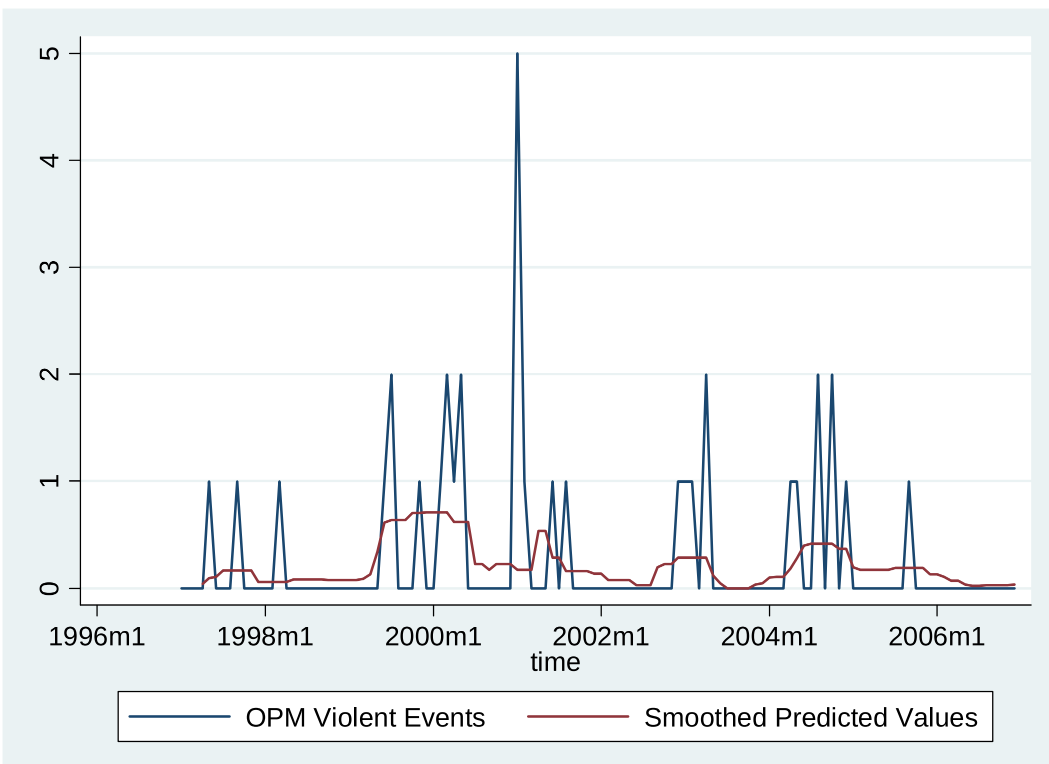


Figure 41: Smoothed Negative Binomial Predicted Values for OPM

We now turn toward our model's ability to forecast the violent activities of the OPM. Figure 42 shows our temporal forecast. While our model does not pick up the beginning of the out-of-sample violent phase it forecasts the core of the phase. It also forecasts the core of the second phase picking up on the beginning and ending of the OPM violent phase. Overall the model's forecast misclassifies five observations – 3 false negatives and 2 false positives. Figures 43 and 44 provide the out-of-sample forecast results for our duration models. The only difference between the two figures is the way in which we display the true duration of the hostile phases of the OPM. In Figure 43 we display the phases as the counter variable we used to model the series. In Figure 44 we simply flattened those out to better see the beginning and ending of the phases. Both figures show how the model predicted values mirrors the phase's out-of-sample. While the model predicts the first phase a bit early, it still is able to illustrate that a violent campaign is going to take place. The prediction for the second out-of-sample phase is also a bit early but again illustrates that a violent OPM campaign is eminent.

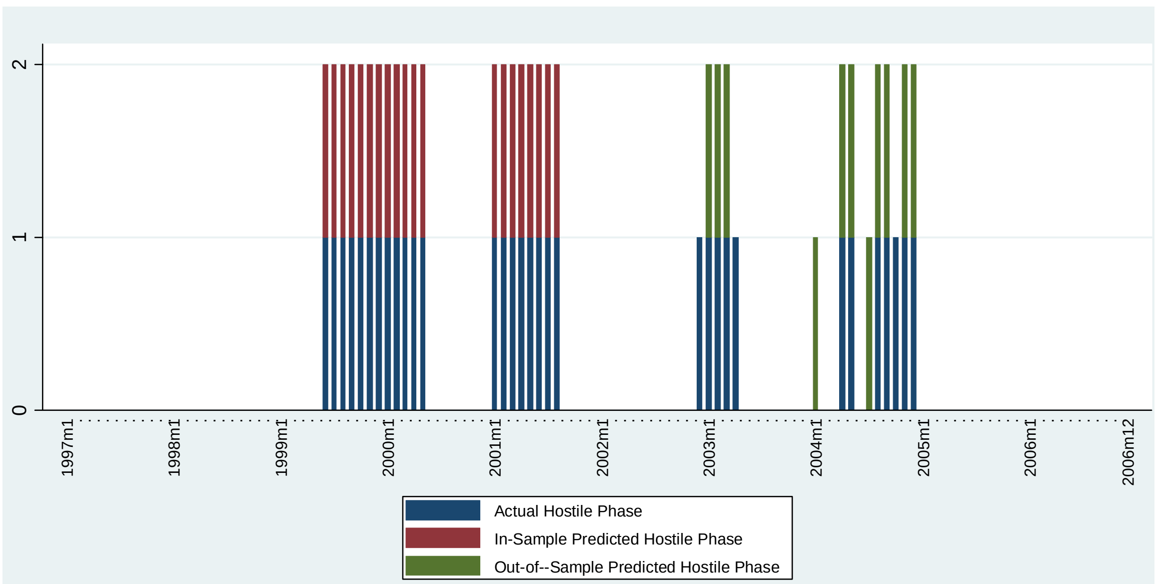


Figure 42: OPM Logit Model Out-of-Sample Forecast

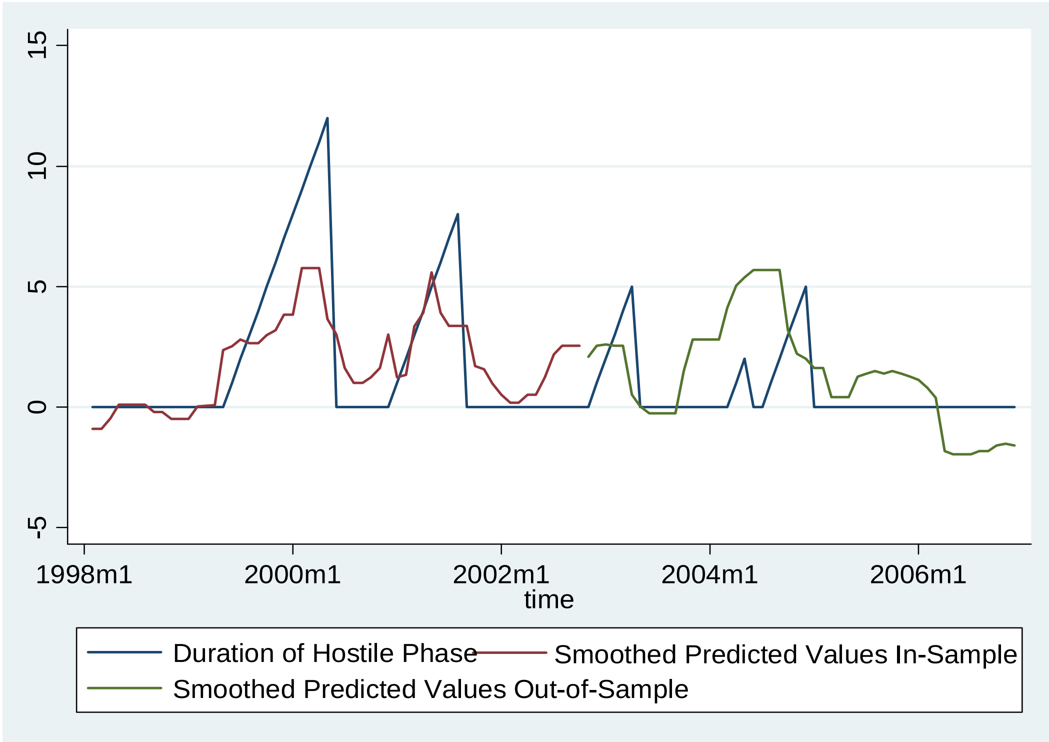


Figure 43: OPM Out-of-Sample Duration Model Smoothed Forecast

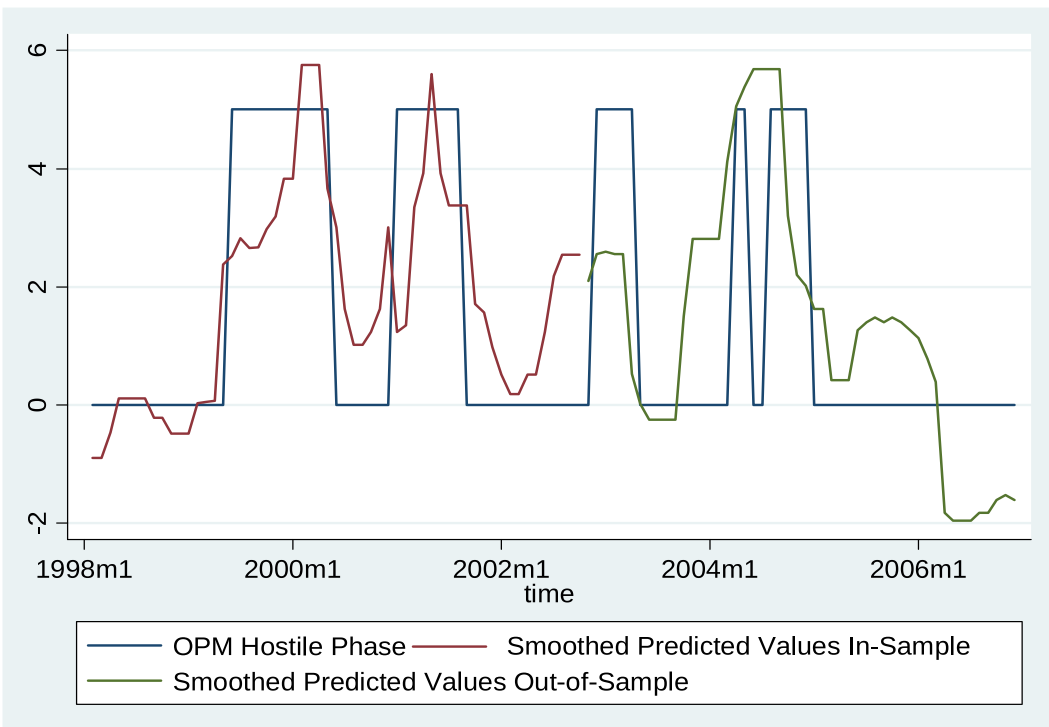


Figure 44: OPM Out-of-Sample Duration Model Smoothed Forecast with Box-Shaped Phases Shown

Overall, our model is a good model of OPM violent phase changes. It is able to anticipate campaigns as well as generate reasonable estimates for when campaigns will begin and end.

4.3 Discussion of Results

In this section, we highlight our findings and make connections across the results for each group. Table 12 summarizes our major findings for each indicator for each group. Not Applicable (NA) represents that the indicator did not enter the model, either because it was not available or because it did not contribute to improving the fit of the model, when we tried it. No refers to no impact, while + and – refer to positive and negative impacts respectively.

Table 12: Summary of Major Findings

	LTTE	*MILF*	*BCL*	*PWG*	*OPM*
unemployment	na	+	na	na	na
food cpi (lagged 1 month)	-	na	-	na	na
FDI (lagged 1 year)	-	-	+	na	na
Other Major Group's Violent Activities	No	+ (NPA)	+ (Awami)	+ (MCC)	+ in recent past; negative in distant past (GAM); + all other separatists)
Government Repression of Other Groups	na	na	positive (BNP towards Awami)	curvilinear (inverted-U)	curvilinear (inverted-U)
Government Repression of GOI	curvilinear (inverted-U)	curvilinear (inverted-U)	curvilinear (inverted-U)	+ in recent past; - in distant past	+
Societal Sentiment towards Government	-	-	-	+	-
Societal Sentiment towards Dissidents	no	+	+	-	+ in recent past; - in distant past

To begin, we found that structural variables did not have much impact on the probability that a group would carry out a violent campaign. Most did not make it into the models and those that did only made a difference in some groups behavior. Unemployment rates, only available for the Philippines, had positive effects on the violent activities of the MILF. The Food prices had negative effects on the violent activities of LTTE and BCL. FDI had negative effects on the violent campaigns of LTTE, MILF, and BCL.

In terms of the activities of other major groups, across the board, positive violent activities by other groups in the recent past yielded a higher probability that the GOI would engage in a violent campaign. The only exception were the activities of the Karuna group in Sri Lanka and as we pointed out, this group split from the LTTE and joined the government in fighting the Tamil Tigers so we would not expect it to have the same impacts as rival separatists groups in the Philippines, India, or Indonesia.

We also included repression of other groups in three of our models and such repressive activities either had positive (BCL) or similar curvilinear effects on the violent campaigns of groups. The last two findings suggest that groups pay attention to the interactions of the state and other competing groups and base their tactical decisions off such interactions.

Repression of the GOI, as hypothesized, is a key factor in explaining and predicting sustained campaigns of violence. We found that, for the most part, repression exhibited a curvilinear effect

on the probability that a GOI would engage in a violent campaign. That is, low and high levels of repression yielded lower probabilities associated with violence, while moderate levels of repression yielded higher probabilities associated with violence. This was the case in three of the five groups (LTTE, MILF, and BCL). The other two groups (PWG and OPM) reacted to higher levels of repression with sustained campaigns of violence of their own. That is, the results produced linear effects – as repression increased so did the probability that the group would engage in a sustained campaign of violence.

Our sentiment variables also had fairly consistent effects on the violent campaigns and activities of our GOIs. Societal support for the government decreased the probability that a GOI would engage in a violent campaign for four of our five groups. The PWG was the exception. Moreover societal support for the dissidents increased the probability that a GOI would carry out a sustained violent campaign. Again, the outlier was the PWG, while sentiment had no impact on LTTE violent campaigns.

Our sentiment data can and should be refined to target specific groups and the activities of the government towards those groups in the future – especially in countries like India and Indonesia where the governments face multiple challengers. Our software is currently being developed to be able to provide such disaggregated information and we hope we'll be able to collect such data for future analyses.

Overall, our findings suggest that government repression, the interactions of the government and other groups, and mass political attitudes are the most important predictors of violent phase changes. We don't think this is surprising and is consistent with our theoretical framework as well as the academic and policy literature on this topic. That said, we have been able to operationalize these factors into disaggregated indicators over time that can be utilized in computational models of politics. Our theories have been calling for such analyses and data for quite some time but until recently most scholars have relied on over-aggregated structural data to examine process oriented theories and models of conflict. Our new data and modeling approaches hopefully will give rise to new studies and analyses focused on the interactions of actors over time and the competition of governments and dissidents over control of the state and support of the population.

In addition, all of our groups were "modelable." That is, our models were able to explain and anticipate their activities with good to excellent accuracy. The average accuracy in terms of classifying observations was 92% ranging from 87% to 97%. Moreover, the sensitivity and specificity were also high indicating that our models could separate the 1's and 0's from each other with high accuracy. No matter what modeling approach we applied (logit, regression of duration, or negative binomial) we were successful in generating series in and out-of-sample that highly represented the true data.

4.4 Conclusion

In this study, we concentrated on modeling the phase changes of five different dissident GOIs in five different countries. Specifically, we examined violent campaigns carried out over the period 1997-2006 by the LTTE (Sri Lanka), MILF (Philippines), BCL (Bangladesh), PWG (India), and

OPM (Indonesia). To specify and estimate our models, we collected new data on group-level and government-level behavior. We also collected new data on political attitudes using automated natural language capabilities. We then compiled structural indicators from various publicly available datasets like the World Bank Development Indicators dataset. We were able to produce five high-quality models based on several indicators of accuracy. We found that, for the most part and as hypothesized, traditional structural indicators were not able to forecast the violent activities of GOIs. Instead, behavioral process variables and mass attitude indicators performed much better in models of sustained violent campaigns by groups over time. Our models were able to explain and forecast such violent campaigns well both in- and out-of-sample.

Having produced useful models of hostile phase changes, Future analyses should address the what-if questions. Now that we know what kinds of variables and models are useful in forecasting the behavior of dissident groups, we need models that can aid in understanding what types of actions the US government can employ to quell such violent campaigns. We suggest a system of equations modeling approach to examine the impacts of US DIME actions on the levers that explain and forecast sustained violent campaigns. Doing so will enable us to see how such actions independently and together can mitigate the variables that lead to sustained dissident violence. Using such an approach we will also be able to examine the second and third order effects of such US strategies and tactics. Moreover, we'll be able to uncover the types of US policies and actions that can tip support in the host government's favor in order to produce stable, peaceful societies.

To demonstrate our proposed approach, we examined the impact of particular US DIME strategies on aggregate measures of separatist and government behavior in India and the Philippines. The aggregate measures are similar to those used as independent variables in the PWG and OPM models above. Specifically we examined the impact of US military training in India and high level US military actions (i.e., show, use, or display of force) in the Philippines. Figure 45 shows the results of estimating a system of equations which examines various low (e.g., appeals, investigations, lawsuits, accusations, criticisms, etc.), medium (e.g., protests, strikes, curfews, demands, etc.) and high (unconventional violence, suicide attacks, skirmishes, abductions, hostage takings, mobilizing forces, imposing blockades, etc.) types of actions by the host government and the separatist groups (which includes PWG) in India. While this figure is a bit daunting to breakdown and examine, it shows the ability to trace the direct, indirect, and total (direct plus indirect) effects of military training on the behavior of the Indian government and the separatist groups it faces. For example, military training positively affects sentiment towards dissidents which increases separatist high hostility (i.e., violence). At the same time, military training directly increases separatist violence.

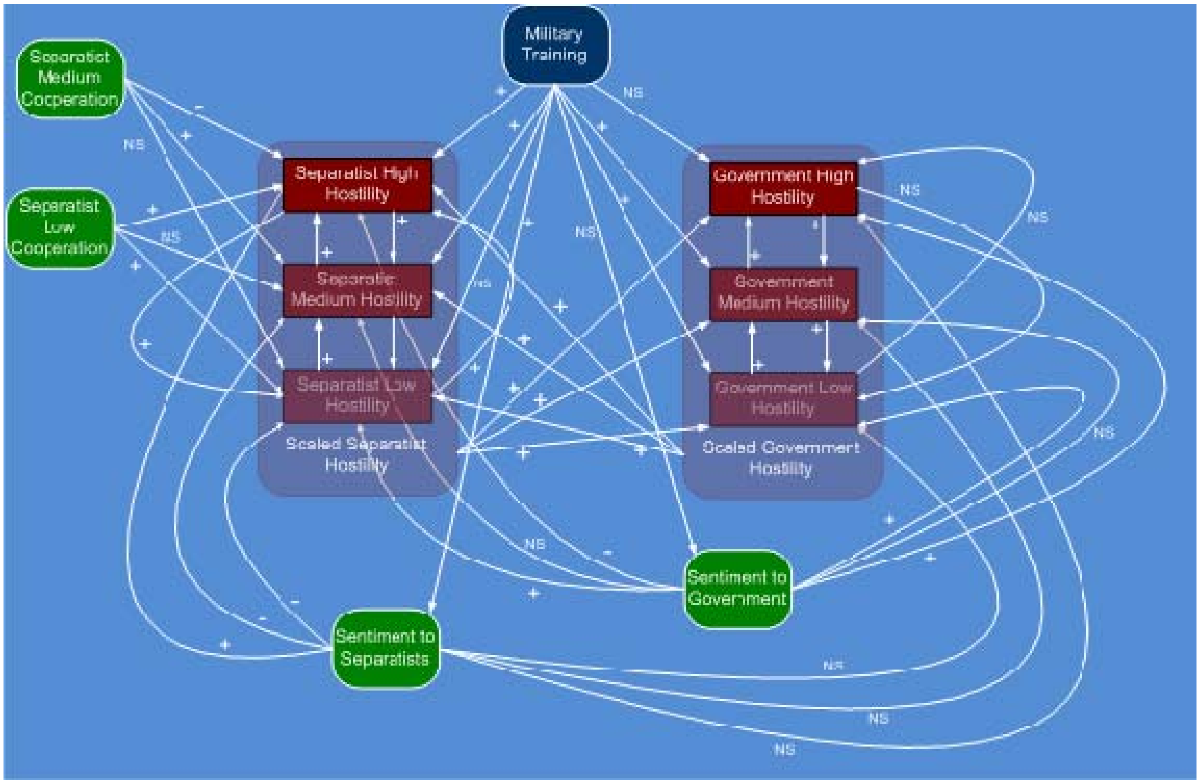


Figure 45: Causal Model of Military Training in India (1997-2006)

We used both time-series impact assessment methods as well as counterfactual methods to examine the impact of such exercises. Figure 46 shows the results of counterfactual analysis of military training on separatist violence in India. We found that US military training increased separatist violent events (controlling for other factors across matched cases) by almost 2 events per month. That is, two fewer events would have transpired per month if US military training had not occurred between 2002 and 2006. Our impact assessment results, depicted in Figure 47 found that while separatist violence tended to increase violence in the beginning of the period, the training eventually decreased violence overall by the end of the exercises.

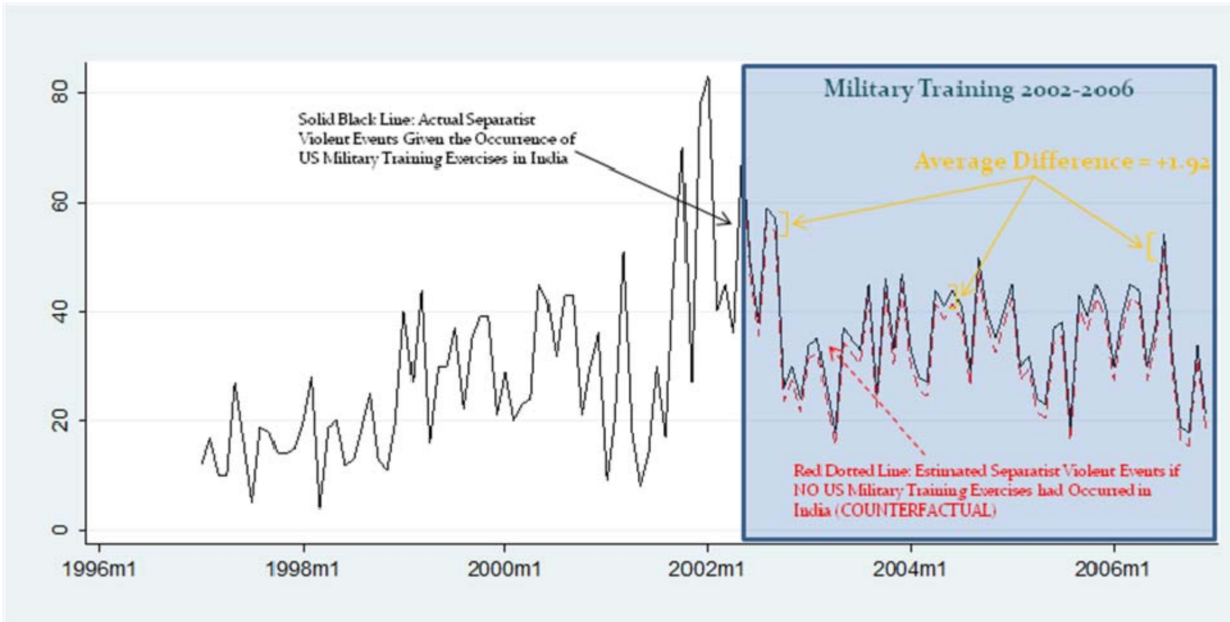


Figure 46: Average Time-Series Effects of US Military Training Exercises on Separatist Violent Events: India 1997-2006

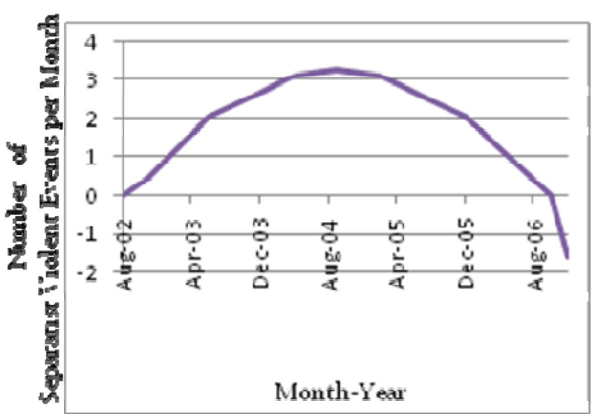


Figure 47: Change in Separatist Violent Events per Month over the Duration of Military Training in India 2002-2006

The above analyses of US DIME actions, specifically military training, help us to understand how US actions affect the levers in our models of violent conflict. In particular we can tie these findings to the analyses of the PWG in India in that increased violence by other separatist groups increased the probability that the PWG would engage in a sustained violent campaign. Moreover, we could argue that based on these findings, US military training probably increased the violent activities of the PWG and we can see that the last two violent phases in our sample carried out by the PWG took place during the period of US military training (2002-2006). We reiterate that we

produced these findings controlling for many other factors and by matching cases across the treatment effect military training much like medical studies of the effects of a medication on a set of patients receiving the medicine and those not receiving the medicine. Moreover, our analyses help us examine how US actions are received by the masses and how those mass attitudes in turn affect the political dynamics in the country of interest. By adding US DIME actions to our models we can better understand what types of actions the US can do to effectively reduce violence in particular countries.

5.0 YEAR TWO

5.1 Sentiment Data: Availability and Aggregation

Sentiment analysis as a field of research is still in development. The dominant method of collecting sentiment data follows a BoWs approach which calculates the number of good and bad words appearing in the text being analyzed, however the resulting sentiment data is generally not attributable to any specific individual or group and is therefore, difficult to put into a meaningful context. We prefer to work with dyadic sentiment data that answers the question, “who is saying what about whom?” Dyadic sentiment can be used to measure individuals’ and groups’ feelings toward their government and its policies. Dyadic sentiment can also tell us about the hearts and minds of the people – whether they are more supportive of the government or of competing dissident groups. However, dyadic sentiment was not available for the present analysis. The sentiment data provided followed the general trend which is the bag-of-words approach. We assumed that the source of sentiment was the news source from which sentiment had been coded.

Sentiment data were provided for 11 sources from January 2002 through the close of 2008, however not all sources were available for this entire period. Qudsway, Al Ahram, Dar al Hayat and Al Yaum were the most complete sources of sentiment available for modeling. Al Manar, Syria News, and Al Ayyam provided the least amount of coverage over the time period. Figure 48 shows the availability of sentiment from the 11 sources.

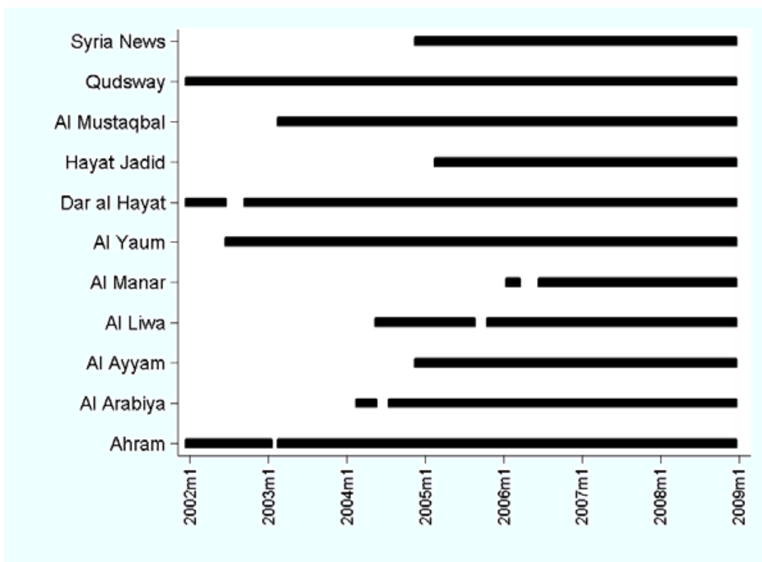


Figure 48: Sentiment Availability by Source

The availability of sentiment data from multiple sources presents interesting theoretical and methodological questions, namely, how can we best make use of the data that is available. We opted for a multi-method approach. We developed a core model for each group of interest and a sentiment model which was run for each sentiment source. We also substituted aggregate measures of sentiment into the sentiment models.

We averaged all sentiment sources together to create aggregate measures of sentiment toward Israel, Palestine, and Lebanon, and the groups of interest. While this approach did extend the availability of sentiment data, sentiment did not appear to significantly increase our ability to model conflict in the region. Our own qualitative research on the sources of sentiment data showed that some sources favored one or more groups of interest and were more critical of others. In other words, it was possible to see large variations in how sentiment was reported by various sources toward groups of interest. This led us to consider how we might aggregate like sources together.

If we think about the sources' affinity / dislike for the countries and groups of interest as a latent variable, we can model the sources' attitudes toward these groups and determine which sources are most similar. Averaging similar sources together will extend the availability of sentiment data and should produce sentiment measures that more accurately reflect the actual data.
Item Response Theory (IRT) has been extensively used in educational testing for scoring the Graduate Record Exam (GRE) and other high-stakes tests (Bennett, Sebrechts, & Yamamoto, 1991). IRT scaling has also been used by social scientists to estimate ideal points for individuals – a subject's true, but unobservable preference about a policy, candidate, political party, etc (Jackman, 2001). IRT relies on Bayesian simulation to estimate a latent variable, in this case "true" relative sentiment toward groups of interest.

IRT take a series of binary inputs as "items" to estimate a latent variable which explains the observed interrelationships in a dataset. Weekly sentiment data was used to construct ratios of good to bad sentiment expressions. A positive number was transformed to a 1 and negative ratios were converted to zeros. A latent variable IRT model was fitted using Markov chain Monte Carlo simulation. See Figure 49 for an example of IRT scaling of the 11 sources over the entire span of the dataset (2002 – 2008).

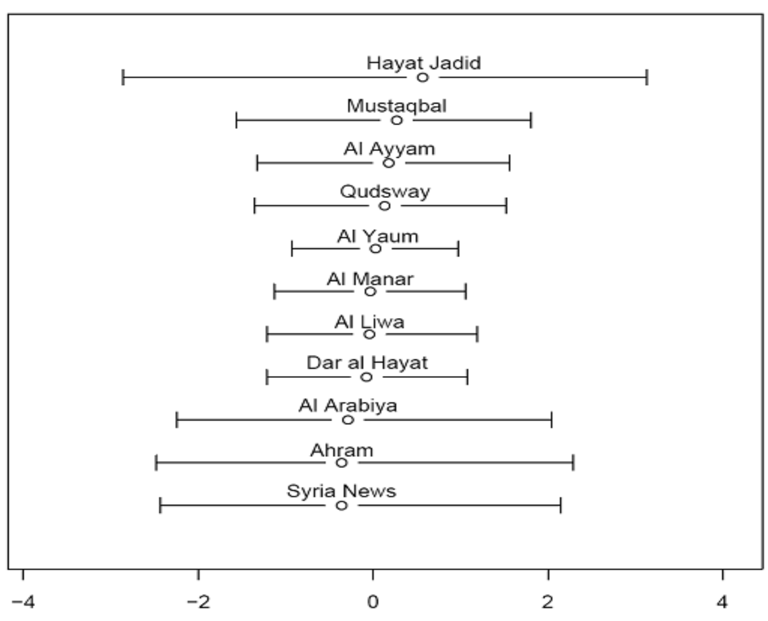


Figure 49: IRT Scaling of Sentiment toward Hamas

The circles in Figure 49 show the "ideal point" estimate of sentiment toward Hamas for each group. The bars to each side of the open circle are confidence intervals, showing the certainty of the ideal point estimate. In this example, we can see that Syria News appears most antagonistic while Hayat Jadid seems to be somewhat positively inclined toward Hamas. However, the large confidence intervals suggest there may not be much difference in the way sentiment is reported by the sources toward Hamas. This scaling was produced using data spanning the entire time period. Additional analyses were conducted at the yearly level to aid in determining which sources should be aggregated to create annual aggregate sentiment measures.

We also used Multi-Dimensional Scaling (MDS), which is often used for exploring the similarities and differences in data and for visualizing relationships in datasets (Cox & Cox, 2008). The most straightforward way to think about MDS is to imagine a 5X5 matrix containing the distances between 5 American cities.

The researcher can specify the number of underlying dimensions - in this case 2 dimensions will produce a two-dimensional "map" of the cities. MDS will arrange the cities according to the specified number of dimensions in a way that best approximates the observed distances in the distance matrix. MDS moves the cities around in 2 dimensional space until a configuration is achieved which best approximates the distances observed in Table 13. MDS can similarly be useful in detecting the underlying dimensions that explain differences between sources in their reported sentiment toward various groups.

Table 13: Distance Matrix of 5 American Cities

	Atlanta	Chicago	Denver	Houston	Los Angeles
Atlanta	0				
Chicago	587	0			
Denver	1212	920	0		
Houston	701	940	879	0	
Los Angeles	1936	1745	831	1374	0

We produced distance matrices similar to Table 13, substituting in our 11 sentiment sources. The distance matrices are square matrices (11X11) representing the absolute distance between the sources on sentiment toward groups of interest. The distances between sources were calculated as the absolute difference of the ratio of good to bad sentiment words per month. Multi-dimensional scaling was then performed on the distance matrices to estimate a scaled ordering of the 11 sources' sentiment toward groups of interest. This scaling represents the observed differences in sources' sentiment toward groups over time. Sources which appeared most similar in their sentiment reporting for each group were aggregated together, giving us an aggregate measure of sentiment covering a longer span of analysis time.

Figures 50-55 show the results of MDS on the 11 sentiment sources toward Israel and Palestine, and four groups of interest. Tight clustering of sources suggests these sources show similarity in the way they report sentiment toward the group of interest. A shotgun pattern would suggest there may be large differences in the way sentiment is reported by the sources.

In Figure 50, it is clear that several sources are similar in their reporting of sentiment toward Israel. Al Arabiya, Al Liwa, Mustaqbal, Dar Al Hayat cluster together, while Qudsway and Hayat Jadid for example, tend to remain on the fringes of the ideological space. Dar Al Hayat and Mustaqbal report sentiment for a majority of the analysis time, so including them in the aggregated sentiment measure ensures that we have increased the availability of sentiment data when modeling sentiment toward Israel.

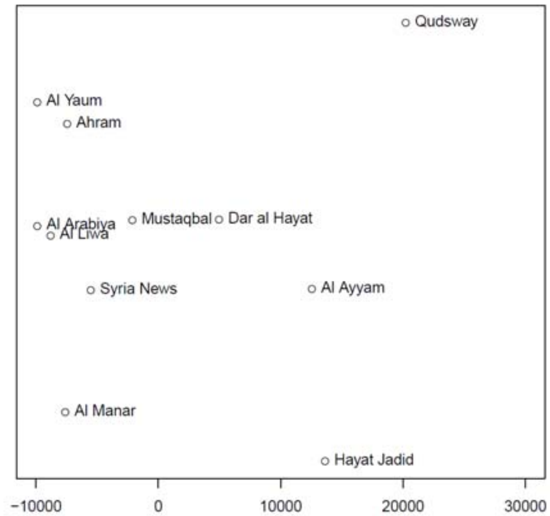


Figure 50: MDS of Sentiment Sources toward Israel

MDS showed that even more sources were similar in their reporting of sentiment toward Palestine. In Figure 51, we see that Hayat Jadid and Al Manar were the major outliers. All other sources tend to cluster at the bottom and left of the ideological space. We again see tight clustering of the sources in Figure 52 which shows the results of MDS on sentiment sources toward Al Aqsa. Qudsway, Hayat Jadid, and Al Ayyam appeared to be the outliers in Figure 52.

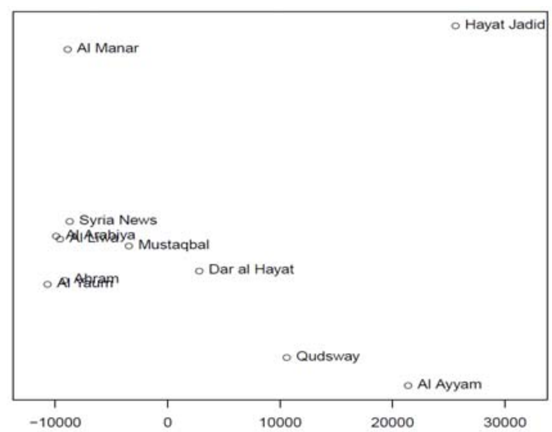


Figure 51: MDS of Sentiment Sources toward Palestine

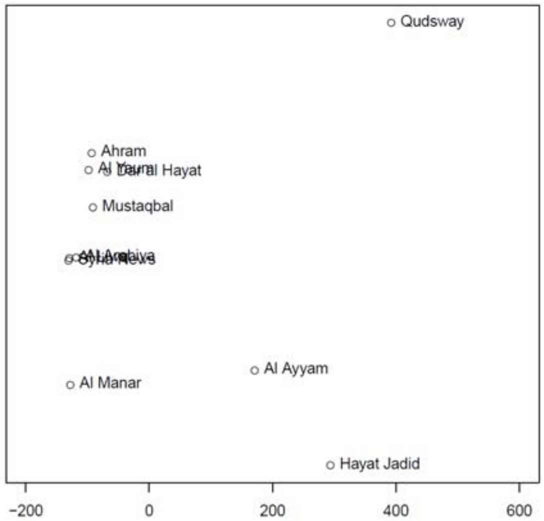


Figure 52: MDS of Sentiment Sources toward Al Aqsa

Qudsway, Al Ayyam, and Hayat Jadid were again spatially distant from other sources in their reporting of sentiment toward Hamas in Figure 53. Seven sources cluster tightly in the easterly part of the spectrum and Al Manar shares this characteristic even though it did not cluster as tightly. MDS revealed major differences in the way sentiment was reported toward Hezbollah in Figure 54. Mustaqbal was a clear outlier, but few sources clustered tightly. This suggests major differences in the way the sources talked about Hezbollah. In Figure 55 we see a much tighter cluster of the sources when reporting on Palestinian Islamic Jihad. Only Hayat Jadid and Qudsway appear to be outliers. The remaining sources tend to cluster together.

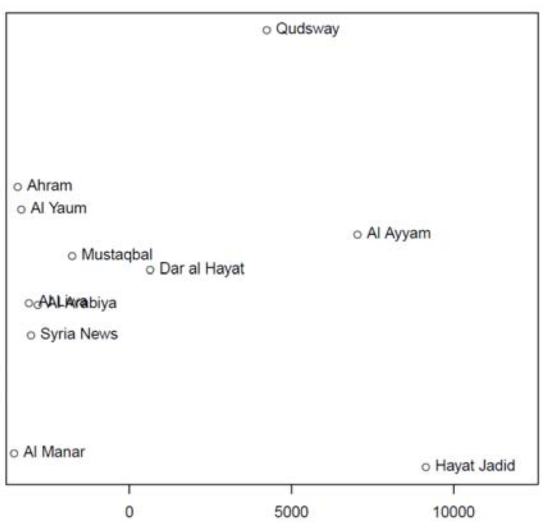


Figure 53: MDS of Sentiment Sources toward Hamas

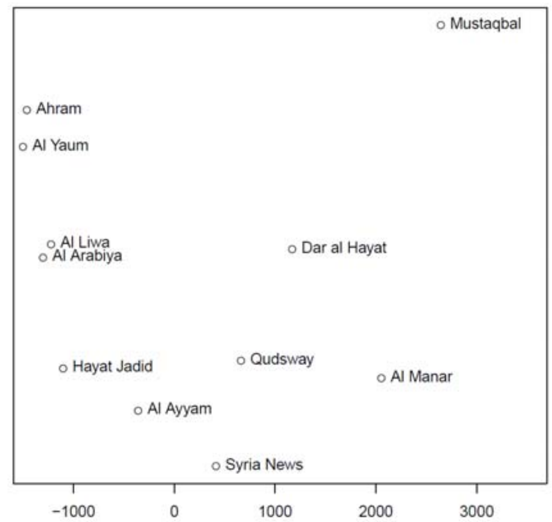


Figure 54: MDS of Sentiment Sources toward Hezbollah

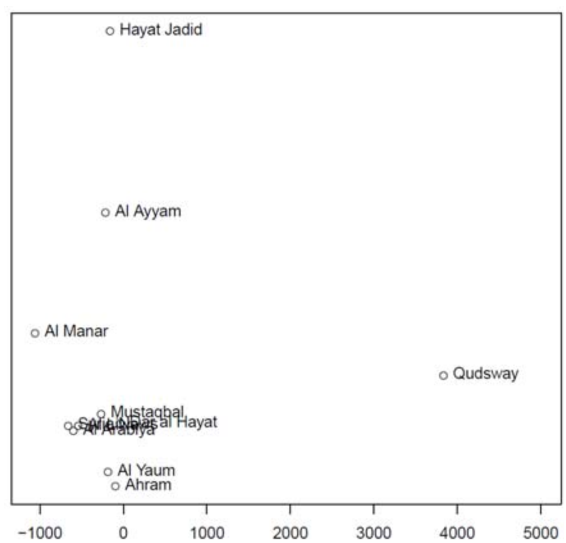


Figure 55: MDS of Sentiment Sources toward Palestinian Islamic Jihad

The graphical summaries of MDS presented in Figures 50-55 were used along with results of IRT analysis, and summary measures for each source, to produce aggregated measures of sentiment toward Israel, Palestine, Lebanon, and each of the groups of interest. Our goal was twofold: produce aggregate sentiment measures that covered a majority of the analysis time, and fairly and accurately reflect the underlying sentiment data.

5.2 Hostile Phases

This section describes how we determined the hostile phases of each group. We used both qualitative historical narratives and quantitative measures of violence to determine each group's hostile phases.

The Second Intifada, sometimes referred to as the Al Aqsa Intifada, began in 2000 as Palestinian-Israeli violence began to intensify. This period has been characterized by massive protests, worker strikes, armed attacks on Israeli soldiers and civilians, suicide bombings, and launching Qassam rockets into Israel by Palestinian forces. Israel responded by tightening curfews, setting up checkpoints, and targeting Palestinian police and prisons.

Palestinian presidential elections were held in January 2005, ushering in Mahmoud Abbas as the new president of the Palestinian Authority. Abbas promoted peaceful negotiation with Israel. After taking office, Abbas ordered Palestinian police to the northern Gaza Strip to prevent further shelling of Israeli settlements. On February 8, 2005, Ariel Sharon and Abbas announced a mutual ceasefire and an effective end to the Second Intifada. Israel adopted the Disengagement Plan, and began luring Israelis out of the Gaza Strip and the northern West Bank. Abbas then entered talks with leaders of Hamas and the Palestinian Islamic Jihad, encouraging an end to hostilities. However, by mid-summer, the Al Aqsa Martyrs' Brigade, Islamic Jihad, and Hamas intensified attacks, shelling Israeli settlements and bombing the city of Sderot.

Hamas won a majority of seats in the Legislative Council in January of 2006 and later that year declared an end to the 2005 ceasefire agreement. The United States and European Union declared Hamas a terrorist organization and began seizing it assets held abroad. Israel began two operations in response to Hamas: Operation Summer Rains (June 2006) and Operation Autumn Clouds (November 2006). Rocket fire from the Gaza Strip into Israeli territory intensified and Israel effectively cut the Gaza Strip in half when it destroyed several bridges. Israel arrested approximately 64 Hamas officials, many of them Palestinian Authority cabinet ministers and government officials. Israel and the Palestinian Authority agreed to a ceasefire late in the year to lick their wounds. No pretensions were made regarding resumption of peace talks.

The 2006 hostile period which included Palestinian rocket launches and two Israeli ground offensives in the Gaza Strip was the most intense period of fighting during the analysis time. Although, the data suggests moderate to high levels of violence occur throughout the 7 year period. Using the available event data, we generated hostile phase variables coded as 1 during periods (months) when a group of interest exhibited hostile behavior toward Israel and 0 during non-hostile periods. The non-hostile periods generally correspond to a time of declared ceasefire, major political events such as an election which temporarily interrupts hostility, or a lull in hostility. We also noticed that some groups direct hostility toward the government or toward the general population but not necessarily both at the same time while others exhibit a more random pattern of violence.

We generated time-series plots of group hostility toward both government and civilian targets and used this to determine hostile phases. We looked for patterns of violence and sustained periods of violence, comparing the data to qualitative accounts of the ongoing conflicts. Figures 56-59 show the average counts of hostile events directed toward the Israeli government and the general population by each group of interest. Hostile phases are shaded on each graph. Determining a hostile phase is part science and part art as each group shows unique patterns of violence in the unfolding conflict.

Al Aqsa hostility is characterized by several critical events. In Figure 56, we see sporadic violence during the Second Intifada until the Sharon and Abbas ceasefire agreement in early 2005. Violence resumes later in 2005 and spikes in 2006 as hostility between the Palestinian Authority and Israel ramps up. Al Aqsa shows very sporadic periods of violence beginning in 2007 when Israel began excavation near the Al Aqsa Mosque.

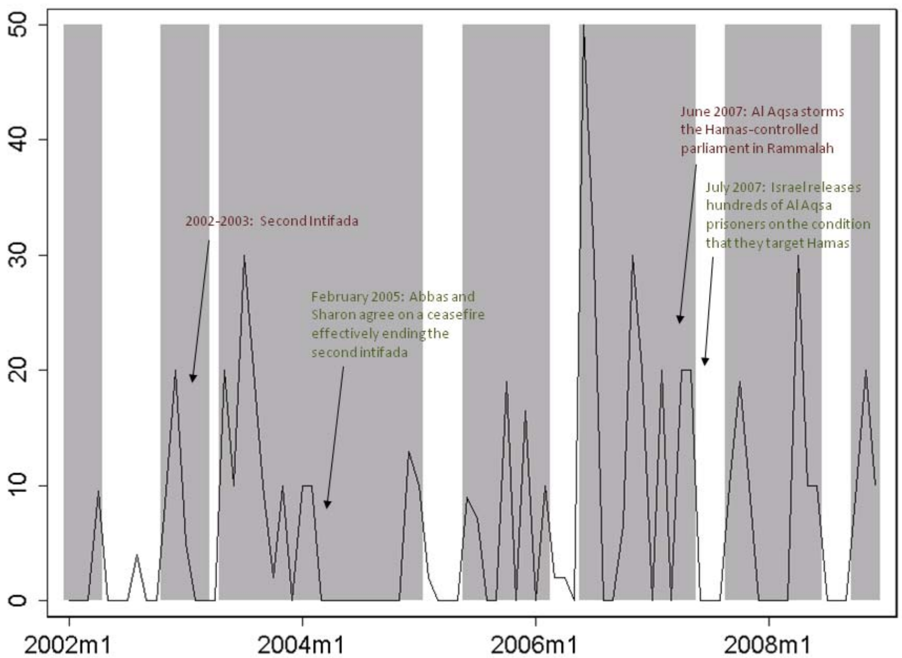


Figure 56: Al Aqsa Hostile Phases

There are few bright spots in the patterns of conflict between Israel and Hamas, shown in Figure 57. Hamas performs well in Palestinian elections during 2005 and 2006 and we see a short period of relatively low hostility. Israel and Hamas reach a ceasefire agreement in late 2006 after heavy violence including Rocket attacks on Israel and two separate Israeli ground offensives in the Gaza Strip and West Bank. Otherwise, the available data suggests that Hamas is generally engaged in hostility against Israel during the entire analysis period.

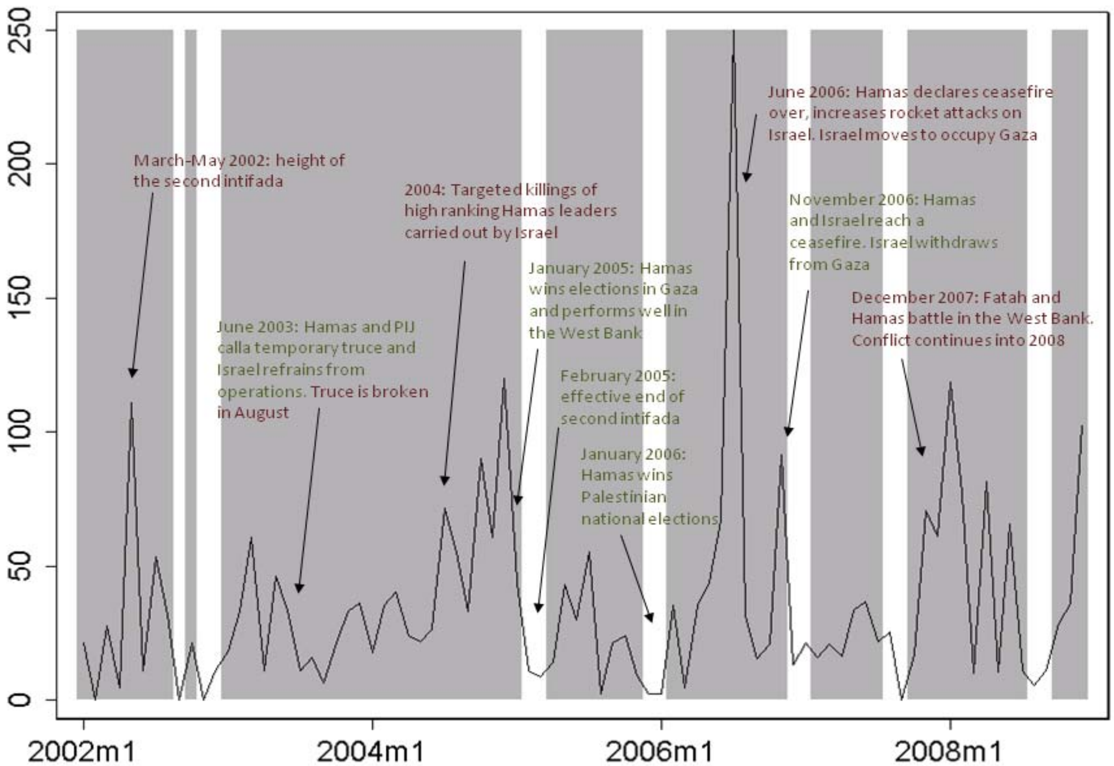


Figure 57: Hamas Hostile Phases

Hezbollah hostility followed a much simpler pattern and fit the basic qualitative accounts of the conflict reported by mass news affiliates. In Figure 58, we see Hezbollah is generally hostile during the time of the Second Intifada, but violence wanes after Hamas won the 2005 election and Abbas and Sharon agreed to a ceasefire. Hezbollah returns to a hostile stance toward Israel during the volatile period which encompassed most of 2006.

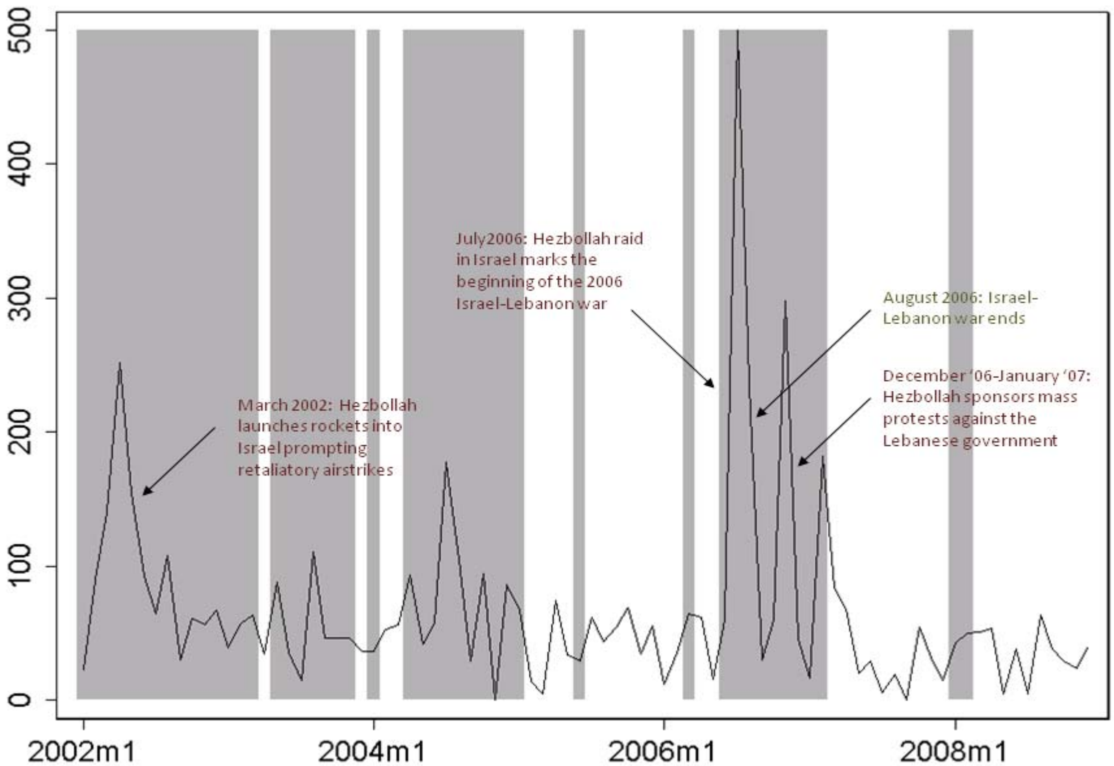


Figure 58: Hezbollah Hostile Phases

The Palestinian Islamic Jihad showed almost the reverse pattern of hostility compared with Hezbollah. In Figure 59, we see low level fighting which characterized the early part of the period. There was a significant decline in hostility just after the Palestinian Authority election introduced Abbas as president in 2005. Violence, however, began to rise in late 2005 and continued through most of 2007. During this period, we again see the spike in violence during 2006 that was present for each group of interest. The group also became violent again in 2008 in response to Israeli airstrikes that killed a number of Islamic Jihad leaders in the Gaza Strip.

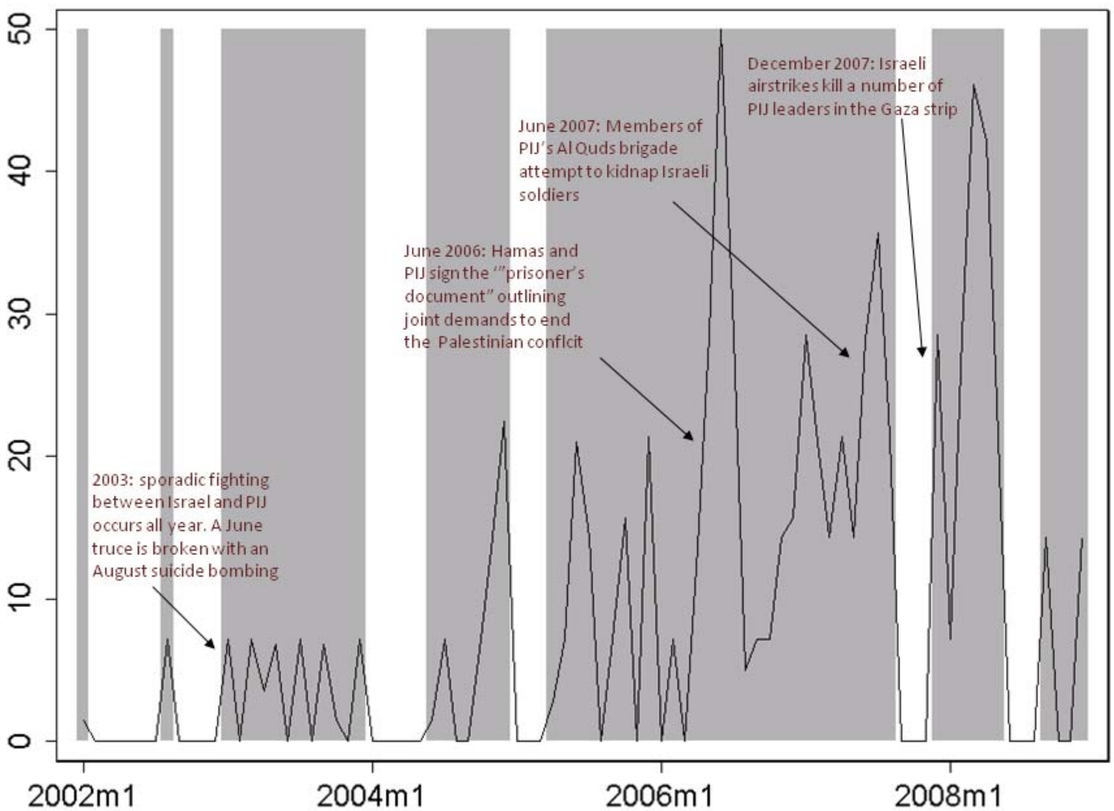


Figure 59: Palestinian Islamic Jihad Hostile Phases

5.3 Base Models All Groups

Our primary goal is to determine when groups of interest will enter a sustained period of violence toward their primary target which in this case is Israel. Therefore we constructed a dependent variable that took on a value of 1 during hostile phases as described above, and a value of 0 during non-hostile periods.

We make use of event data, the "day-by-day coded accounts of who did what to whom as reported in the open press" (Goldstein, 1992, 369), to develop measure of conflict and cooperation between groups of interest, Israel, Palestine, and Lebanon. The competing groups hypothesis, as outlined in our first Cascading Air Power Effects Simulation (CAPES) study, suggests that groups compete over resources and as one group intensifies its violent actions, other groups must do so as well. Because our groups of interest all operate within a small, well-defined region and primarily target Israel, we have reason to believe groups engage in competition and therefore include variables that count the violent actions by all other groups of interest in our models.

We also created measures of Israeli repression toward individual groups of interest from the event data. Some researchers argue that high and low levels of repression yield low levels of dissent. Dissenting behavior is difficult when repression is low, since there is nothing to dissent. And dissenting is difficult when repression is high. However, at medium levels of state repression groups have opportunity and ability to engage in dissenting behavior. We should observe increasing group violence as repression increases until it reaches a tipping point, at which point, the costs of dissenting become too great and groups disengage in violent actions. We include a squared term for *Israel repression to group of interest* in our models to test this theory. If our hypothesis is supported, the non-squared term should be positive and significant and the second squared term should be negative and significant.

Table 14 presents results from the base models of hostility toward Israel for each group. Two models are presented for each group of interest; starred models differ only in that they include a squared term for Israeli hostility toward the group of interest which captures the curvilinear effect of state repression. Israeli repression is significant in three of the four models. In the model of Al Aqsa hostility, Israeli repression toward Hamas and Palestinian Islamic Jihad are positive and significant which suggests that as Israel engages in conflict with those two groups, Al Aqsa is more likely to initiate hostility toward Israel.

Table 14: Base Models for All Groups

	Al Aqsa	Al Aqsa*	Hamas	Hamas*	Palestinian Islamic Jihad	Palestinian Islamic Jihad*	Hezbollah	Hezbollah*
Al Aqsa to Israel Hostility			-0.0003	-0.0004	0.0012	0.0012	0.0311	0.0371
Hamas to Israel Hostility	0.0042	0.0047			0.0185	0.0188	0.0191	0.0164
PIJ to Israel Hostility	0.0046	0.0048	-0.0115	-0.011			0.0103	0.01
Hezbollah to Israel Hostility	0.004	0.0037	0.0272	0.0269	0.0119	0.0119		
Lebanon to Israel Hostility	-0.0786	-0.0819			0.9672	0.9796	**0.4987***	**0.5375***
Palestine to Israel Hostility	-0.0237	-0.025	0.0326	0.0317	0.0224	0.0226	-0.0066	-0.0043
Israel to Al Aqsa Hostility	0.0026	-0.0104	-0.0019	-0.0021	0.0038	0.0044	0.0118	0.0066
Israel to Al Aqsa Hostility2		0.0001						
Israel to Hamas Hostility	**0.0127***	**0.0133****	0.009	0.0043	0.0002	0.0002	**-0.0075***	**-0.0071***
Israel to Hamas Hostility2				0				
Israel to PIJ Hostility	**0.0731****	**0.0765****	0.0221	0.0226	**0.0412***	0.0297	0.0072	0.0077
Israel to PIJ Hostility2						0.0002		
Israel to Hezbollah Hostility	0.0104	0.0092	0.0047	0.0039	**-0.0349***	**-0.0352***	0.0196	-0.0158
Israel to Hezbollah Hostility2								0.0004
Constant	-1.2548	-1.1523	-2.1521*	-2.0269	0.6901	0.7605	-5.4355***	-5.3639***
N	84	84	74	74	84	84	84	84
Percent Correctly Predicted	78.57143	77.38095	86.48649	86.48649	83.33334	83.33334	88.09524	86.90476
Percent Correct Positives	93.75	93.75	96.72131	96.72131	93.33334	93.33334	86.95652	86.95652
Percent Correct Negatives	30	25	38.46154	38.46154	58.33333	58.33333	89.47369	86.8421

*Models with an additional squared term for Israeli hostility toward the group of interest.

The Palestinian Islamic Jihad (PIJ) likewise responds to Israeli repression. As Israeli violence toward PIJ increases, PIJ responds by initiating a period of hostility. Israeli repression of Hezbollah, however, appears to be associated with a lower probability of PIJ hostility toward Israel. We can see one possible explanation for this unlikely finding by looking at Figures 58 and 59. Hezbollah appears most hostile during the early part of the data set, but PIJ violence escalates much later. We suspect the increased violent activity of the PIJ at a time when our data suggests Hezbollah is engaging in relatively lower levels of violence explains this finding. As could be expected, the likelihood of Hezbollah entering a violent phase increases as the conflict between Lebanon and Israel escalates. Indeed the Lebanon War of 2006 was a major event driving the violent behavior of all groups of interest.

The model for Hamas appears to fit about as well as other models; the percent correctly predicted is on par with other models and the model does a similarly good job of predicting hostile and non-hostile phases. However none of the variables turned out to be significant predictors of Hamas' hostile phases. As already noted, the data on Hamas' violent activities toward Israel suggests it is always in a hostile phase during the analysis period, with short-lived periods of relative peace being the exception to the rule.

Our model of Hezbollah seems to be the best fitting model of the four groups given that we classify the positive and negative cases equally as well. The other groups' models tend to do poorly on the negative cases.

5.4 Sentiment Models All Groups

In this section we present models for each group of interest using good sentiment toward groups, bad sentiment toward groups, and finally the best performing aggregate sentiment measure. We developed our sentiment models using the base models presented above. Unfortunately, the sentiment data available for this analysis followed the general trend of reporting only bag of words sentiment as reported by news sources. It was difficult to put this sentiment into a meaningful context for analysis and the results were rather lackluster. Sentiment did in some cases increase our ability to correctly predict hostile and non-hostile phases, but the improvement was only marginal, often resulting in models with no significant variables. The models that tend to be the best in terms of explanation and prediction are the models that use incomplete data due to source coverage. These models are not really comparable to the base models and other models with 70 observations or more. For example the Al Manar (column 6) model in Table 15 correctly classifies 100% of the data points, but it only models 32 observations. Thus, we disregard the model results that do not include at least 70 observations in term of our comparisons and analysis.

Table 15: Al Aqsa Sentiment Models: Good Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Hamas to Israel Hostility	0.0047	0.0016	4.6689	0.0297	0.0761	0.4451	0.0301	0.0098	0.1234	0.0185	0.0068	0.1567
Hezbollah to Israel Hostility	0.0037	0.0080	-1.3328	-0.0090	-0.0199	0.0629	0.0038	0.0015	-0.0202	0.0079	0.0021	-0.0098
PIJ to Israel Hostility	0.0048	0.0227	-32.4922	-0.0498	-0.0197	-1.6246	-0.0148	-0.0217	-0.1028	**-0.0805***	-0.0219	-0.0947
Lebanon to Israel Hostility	-0.0819	-0.0706	-76.7865	-0.2821	0.3636	-13.1503	-0.2159	-0.2291	-0.1575	-0.2927	-0.2119	0.3509
Palestine to Israel Hostility	-0.0250	-0.0282	-13.1410	-0.0653	-0.0927	0.4171	-0.0364	-0.0327	-0.1488	0.0150	-0.0316	-0.1295
Israel to Al Aqsa Hostility	-0.0104	0.0089	-38.4246	-0.0587	0.0065	1.2141	0.1020	0.0344	0.0344	-0.0166	-0.0016	-0.0231
Israel to Al Aqsa Hostility2	0.0001	0.0000	1.4684	0.0032	0.0024	0.0056	-0.0013	0.0001	0.0009	0.0023	0.0001	0.0041
Israel to Hamas Hostility	**0.0133****	**0.0130***	17.2603	**0.0514***	0.0232	0.3055	0.0128	**0.0267****	0.0414	0.0159	0.0117	0.0113
Israel to Hezbollah	0.0092	0.0128	-5.4938	0.0304	0.0385	-0.8926	0.0189	0.0243	0.0170	0.0127	0.0135	-0.0582
Israel to PIJ	**0.0765****	**0.0746****	49.4963	**0.1476***	0.1982	0.1403	0.0581	**0.1207****	0.1143	0.0715	**0.0881****	0.3217
Israel to Lebanon	0.0170	0.0177	0.8290	-0.0128	0.0277	0.4395	0.0163	0.0010	0.0137	0.0303	0.0216	0.0173
Israel to Palestine	-0.0005	-0.0004	3.9403	0.0199	0.0226	0.2303	-0.0006	-0.0005	0.0272	0.0085	0.0011	**0.0315***
Good Sentiment to Al Aqsa			-233.5954	-0.1411	1.1008	-3.1930	0.0800	-0.2799	-0.0909	-0.1720	0.0171	0.2352
Good Sentiment to Israel		0.0039	1.3130	0.0006	0.0068	-0.0502	-0.0109	**0.0030****	-0.0010	**-0.0061***	-0.0005	0.0053
Good Sentiment to Palestine		-0.0086	0.3500	0.0001	-0.0350	-0.0800	-0.0026	0.0000	0.0003	-0.0002	0.0017	-0.0295
Constant	-1.1523	-1.0186	-1210.0000	-4.0388	-1.9994	22.7164	-0.7923	-5.9072***	-0.4411	2.1121	-3.9092**	-1.6378
N	84	83	56	49	53	32	78	81	46	70	84	49
Percent Correctly Predicted	77.38	79.52	100.00	85.71	90.57	100.00	80.77	90.12	84.78	90.00	83.33	91.84
Percent Positives Correct	93.75	92.06	100.00	91.67	92.50	100.00	91.67	96.88	94.12	94.64	92.19	97.22
Percent Negatives Correct	25.00	40.00	100.00	69.23	84.62	100.00	44.44	64.71	58.33	71.43	55.00	76.92

We followed two modeling strategies for including sentiment variables in our models of group hostility toward Israel. First, we modeled group hostility using each of the 11 different sentiment sources. In a number of cases, this strategy yielded models that over-fit the data, meaning that the model could not correctly be estimated. In most cases this was due to missing sentiment data (data was not available for all 11 sources over the entire analysis period).

We also noticed that in some models, the effect of sentiment varied by source. This is potentially due to the differences in how sentiment is reported by the individual sources. After conducting some qualitative research on the media sources used for sentiment data, we believe conflicting results like this may be explained by differences in the way sources report sentiment. For example, Dar al Hayat is a widely read Arab newspaper with a circulation of almost 300,000. Al Manar is the satellite television station of Hezbollah. And Al Yaum is the first Russian television news channel to broadcast in Arabic. These sources represent divergent view points and likely take different positions on the ongoing Israeli-Palestinian conflict. We can also safely assume that writing styles, article lengths, and even column space devoted to certain aspects of the conflicts differ among the 11 sources, especially since they are writing for divergent audiences.

We have attempted to compensate for some of these differences by rescaling the sentiment variables and by using additional techniques such as multi-dimensional scaling and IRT scaling to develop rescaled aggregate sentiment measures. While these techniques have extended the available data for modeling purposes, the aggregate measures failed to produce substantially better results than simply relying on one or two of the sentiment sources which did have adequate available data.

Tables 15-26 document our efforts to model good sentiment toward groups, bad sentiment toward groups, and aggregate sentiment toward groups. The inclusion of sentiment variables in the models did not drastically alter the results of the base model; variables that were significant in the base models generally remained significant in the sentiment models. Sentiment variables were significant in some of the individual models.

Table 16: Al Aqsa Sentiment Models: Bad Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Hamas to Israel Hostility	0.0047	-0.0003	0.0355	0.0234	0.0655	-0.1022	0.0368	0.0179	0.1846	0.0398	0.0078	16.3323
Hezbollah to Israel Hostility	0.0037	0.0067	-0.0040	0.0010	-0.0140	0.9890	0.0046	-0.0041	-0.0382	0.0133	0.0019	-0.1027
PIJ to Israel Hostility	0.0048	0.0281	-0.0581	-0.0259	-0.0037	-2.6354	-0.0009	-0.0239	-0.1318	**-0.1130***	-0.0226	-5.7063
Lebanon to Israel Hostility	-0.0819	-0.0585	-0.0986	-0.0779	0.2754	-24.1960	-0.1827	-0.1578	-1.2753	-0.3737	-0.1854	56.5832
Palestine to Israel Hostility	-0.0250	-0.0328	-0.0670	-0.0427	-0.0625	1.6507	**-0.0462***	-0.0405	-0.0840	0.0118	-0.0265	-6.1513
Israel to Al Aqsa Hostility	-0.0104	0.0041	-0.1502	-0.1212	-0.0137	-0.6475	0.0867	0.0249	0.2890	0.0731	-0.0338	4.9691
Israel to Al Aqsa Hostility2	0.0001	0.0000	0.0056	0.0051	0.0026	0.0304	-0.0010	0.0003	-0.0041	0.0017	0.0003	0.1946
Israel to Hamas Hostility	**0.0133****	**0.0147****	0.0249	**0.0333***	0.0206	0.3701	0.0131	**0.0301****	0.0510	0.0279	0.0132	-1.7205
Israel to Hezbollah	0.0092	0.0110	-0.0111	0.0103	0.0022	-1.9998	0.0133	0.0330	0.0381	0.0016	0.0085	-4.4298
Israel to PIJ	**0.0765****	**0.0810***	**0.1890***	0.1309	0.1463	-0.3162	0.0598	**0.1428***	0.1485	0.1246	0.0816*	15.7208
Israel to Lebanon	0.0170	0.0165	0.0028	-0.0053	0.0246	0.8338	0.0157	-0.0065	0.0303	0.0272	0.0186	3.5923
Israel to Palestine	-0.0005	-0.0007	**0.0200***	0.0136	0.0207	0.4484	-0.0003	-0.0014	0.0243	0.0115	0.0023	3.7890
Bad Sentiment to Al Aqsa			-0.1611	-0.0374	0.5735	5.3299	-0.0815	**-0.1446****	-0.0216	**-0.3094****	**0.0312****	-40.8882
Bad Sentiment to Israel		0.0004	0.0081	0.0007	0.0045	-0.0320	0.0051	**0.0017****	0.0000	-0.0017	0.0004	0.5386
Bad Sentiment to Palestine		-0.0066	-0.0083	-0.0012	-0.0238	-0.1563	-0.0119	-0.0003	-0.0043	-0.0004	-0.0006	-2.8165
Constant	-1.1523	-0.5914	-4.9316**	-3.3047	-2.0190	43.2134	-1.0023	-5.7910***	7.2447	-0.9576	-4.9947***	-442.3947
N	84	83	56	49	53	32	78	81	46	70	84	49
Percent Correctly Predicted	77.38	75.90	87.50	87.76	84.91	100.00	83.33	88.89	84.78	94.29	84.52	100.00
Percent Positives Correct	93.75	92.06	93.02	94.44	90.00	100.00	91.67	96.88	91.18	96.43	92.19	100.00
Percent Negatives Correct	25.00	25.00	69.23	69.23	69.23	100.00	55.56	58.82	66.67	85.71	60.00	100.00

Table 17: Al Aqsa Aggregated Sentiment Model

	Base	Sentiment
Hamas to Israel Hostility	0.0047	0.0025
Hezbollah to Israel Hostility	0.0037	0.0042
PIJ to Israel Hostility	0.0048	-0.0157
Lebanon to Israel Hostility	-0.0819	-0.1498
Palestine to Israel Hostility	-0.0250	-0.0248
Israel to Al Aqsa Hostility	-0.0104	-0.0298
Israel to Al Aqsa Hostility2	0.0001	0.0003
Israel to Hamas Hostility	**0.0133****	**0.0153***
Israel to Hezbollah	0.0092	0.0032
Israel to PIJ	**0.0765****	**0.0907****
Israel to Lebanon	0.0170	0.0218
Israel to Palestine	-0.0005	-0.0004
Bad Sentiment to Al Aqsa		**-0.0632****
Bad Sentiment to Israel		-0.7630
Constant	-1.1523	-2.5015**
N	84	84
Percent Correctly Predicted	77.38	83.33
Percent Positives Correct	93.75	93.75
Percent Negatives Correct	25.00	50.00

Table 18: Hamas Sentiment Models: Good Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Al Aqsa to Israel Hostility	-0.0004	-0.0065	-0.0274	-0.0077	-0.0342	-1.5984	-0.0130	-0.0204	0.0082	0.0339	-0.0208	0.0043
Hezbollah to Israel Hostility	0.0269	**0.0388***	0.0283	0.0435	0.0213	0.2973	0.0333	0.0232	0.0251	0.0200	0.0243	0.0569
PIJ to Israel Hostility	-0.0110	-0.0331	-0.0465	-0.0251	-0.0755	-1.0171	0.0161	-0.0303	-0.0195	-0.0665	-0.0039	-0.0812
Palestine to Israel Hostility	0.0317	0.0667	0.0487	0.0333	0.0759	0.9762	0.0270	0.0394	0.0457	0.0418	0.0334	0.0803
Israel to Al Aqsa Hostility	-0.0021	0.0215	0.0171	0.0387	0.0430	0.6472	-0.0388	0.0407	0.0165	0.0418	-0.0012	0.0270
Israel to Hamas Hostility	0.0043	0.0197	0.0062	-0.0059	0.0035	0.5661	0.0128	0.0054	0.0041	0.0008	0.0081	-0.0010
Israel to Hamas Hostility2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Israel to Hezbollah Hostility	0.0039	0.0015	0.0065	-0.0001	0.0146	-0.4724	-0.0032	0.0137	0.0190	0.0055	0.0053	0.0143
Israel to PIJ Hostility	0.0226	0.0332	0.0674	0.0903	0.0690	-0.1298	0.0139	0.0284	0.0675	**0.0833***	0.0183	0.0911
Israel to Lebanon Hostility	0.0358	0.0357	**0.0562***	0.0615	**0.0740***	0.7382	0.0346	0.0319	0.0421	0.0650	0.0310	**0.0796***
Israel to Palestine Hostility	-0.0004	0.0035	0.0065	0.0063	0.0079	0.1575	-0.0044	0.0000	0.0061	0.0074	0.0015	0.0019
Good Sentiment to Hamas		**-0.0754****	0.0030	0.0007	0.0191	-0.0568	0.0078	0.0003	-0.0008	0.0048	-0.0015	0.0148
Good Sentiment to Israel		**-0.0031***	-0.0012	0.0018	-0.0027	-0.0488	0.0317	0.0016	0.0014	-0.0003	0.0009	0.0015
Constant	-2.0269	-2.8462*	-4.5842**	-10.0371**	-6.0288*	-43.3309	-3.2227*	-5.0178**	-7.6121*	-5.0822*	-4.1240*	-7.8944*
N	74	73	49	42	46	25	69	71	39	62	74	42
Percent Correctly Predicted	86.49	89.04	89.80	85.71	84.78	100.00	86.96	85.92	87.18	93.55	83.78	88.10
Percent Positives Correct	96.72	96.67	97.44	93.75	91.67	100.00	96.43	94.92	93.33	100.00	95.08	96.88
Percent Negatives Correct	38.46	53.85	60.00	60.00	60.00	100.00	46.15	41.67	66.67	60.00	30.77	60.00

Table 19: Hamas Sentiment Models: Bad Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Al Aqsa to Israel Hostility	-0.0004	-0.0135	-0.0271	0.1666	-0.0286	-1.6968	0.0053	-0.0299	0.0730	0.0337	-0.0414	0.2733
Hezbollah to Israel Hostility	0.0269	**0.0494****	0.0286	-0.0117	0.0214	0.4255	0.0243	0.0201	0.0358	0.0212	0.0224	0.0777
PIJ to Israel Hostility	-0.0110	-0.0104	-0.0472	-0.2234	-0.0685	-1.2235	0.0048	-0.0332	-0.0292	-0.0793	-0.0149	-0.2302
Lebanon to Israel Hostility												
Palestine to Israel Hostility	0.0317	0.0557	0.0446	0.0877	0.0588	1.0079	0.0305	0.0572	0.0226	0.0400	0.0479	0.1641
Israel to Al Aqsa Hostility	-0.0021	0.0296	0.0190	0.3722	0.0418	0.8981	-0.0248	0.0414	0.0669	0.0526	0.0003	0.1551
Israel to Hamas Hostility	0.0043	0.0107	0.0036	-0.1292	0.0035	0.7335	0.0097	0.0131	-0.0142	0.0011	0.0077	-0.0038
Israel to Hamas Hostility2	0.0000	0.0000	0.0000	0.0001	0.0000	0.0006	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Israel to Hezbollah Hostility	0.0039	0.0097	0.0033	-0.0640	0.0154	-0.3374	0.0004	0.0222	0.0166	0.0076	0.0100	0.0562
Israel to PIJ Hostility	0.0226	0.0459	0.0747	0.1729	0.0751	-0.4858	0.0126	0.0181	0.1082	**0.0770***	0.0034	0.1478
Israel to Lebanon Hostility	0.0358	**0.0475***	**0.0547***	0.1807	**0.0711****	0.4582	**0.0406***	0.0295	**0.0919***	0.0790	0.0442	0.1770
Israel to Palestine Hostility	-0.0004	0.0029	0.0072	0.0861	0.0088	0.1434	-0.0037	-0.0003	0.0039	0.0078	0.0042	-0.0064
Bad Sentiment to Hamas		**-0.0227***	0.0008	-0.0017	0.0116	-0.0254	0.0065	-0.0004	0.0013	0.0042	-0.0003	0.0475
Bad Sentiment to Israel		**-0.0051***	0.0005	0.0075	-0.0009	-0.0213	0.0063	**0.0012***	0.0004	-0.0009	**0.0004***	0.0002
Constant	-2.0269	-2.9464*	-4.7366**	-55.3858	-6.0190*	-40.2005	-2.4424*	-6.1840**	-11.0391*	-4.3609*	-8.3770**	-16.6486
N	74	73	49	42	46	25	69	71	39	62	74	42
Percent Correctly Predicted	86.49	87.67	89.80	92.86	84.78	100.00	89.86	85.92	89.74	91.94	86.49	92.86
Percent Positives Correct	96.72	93.33	97.44	96.88	91.67	100.00	98.21	94.92	96.67	98.08	93.44	100.00
Percent Negatives Correct	38.46	61.54	60.00	80.00	60.00	100.00	53.85	41.67	66.67	60.00	53.85	70.00

Table 20: Hamas Aggregated Sentiment Model

	Base	Sentiment
Al Aqsa to Israel Hostility	-0.0004	0.0004
Hezbollah to Israel Hostility	0.0269	0.0263
PIJ to Israel Hostility	-0.0110	-0.0109
Lebanon to Israel Hostility		
Palestine to Israel Hostility	0.0317	0.0324
Israel to Al Aqsa Hostility	-0.0021	0.0000
Israel to Hamas Hostility	0.0043	0.0065
Israel to Hamas Hostility2	0.0000	0.0000
Israel to Hezbollah Hostility	0.0039	0.0047
Israel to PIJ Hostility	0.0226	0.0223
Israel to Lebanon Hostility	0.0358	0.0347
Israel to Palestine Hostility	-0.0004	-0.0006
Bad Sentiment to Hamas		-0.2516
Bad Sentiment to Israel		-0.1939
Constant	-2.0269	-2.1444
N	74	74
Percent Correctly Predicted	86.49	87.84
Percent Positives Correct	96.72	96.72
Percent Negatives Correct	38.46	46.15

Table 21: Palestinian Islamic Jihad Sentiment Models: Good Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Al Aqsa to Israel Hostility	0.0012	-0.0073	0.0005	-0.0995	-0.1497	-2.4231	-0.0207	-0.0243	-0.3364	-0.0019	0.0053	-0.0398
Hamas to Israel Hostility	0.0188	0.0205	0.0055	0.0433	-0.0659	-0.4652	**0.0371***	0.0204	-0.0695	0.0026	0.0185	-0.0100
Hezbollah to Israel Hostility	0.0119	0.0108	0.0333	0.0555	0.0882	0.1278	**0.0450****	0.0140	0.0861	0.0277	0.0138	0.0308
Lebanon to Israel Hostility	0.9796	1.0244						0.6410			1.0488	
Palestine to Israel Hostility	0.0226	0.0211	0.0360	-0.0274	**0.0770***	1.6401	**0.0438***	0.0240	0.0928	**0.0506****	0.0220	0.0192
Israel to Al Aqsa Hostility	0.0044	0.0063	0.1192	0.2598	0.1117	2.1781	**0.0738****	0.0049	0.2332	0.0706	0.0043	0.1089
Israel to Hamas Hostility	0.0002	0.0005	-0.0036	0.0042	**0.0453***	0.0081	-0.0046	-0.0025	-0.0016	-0.0015	0.0009	0.0025
Israel to Hezbollah Hostility	**-0.0352***	-0.0312	-0.0162	-0.1064	**-0.1048***	-0.2329	-0.0388	**-0.0327***	-0.0077	-0.0313	**-0.0339***	-0.0251
Israel to PIJ Hostility	0.0297	0.0410	-0.0164	-0.1252	-0.3997	-5.1903	-0.0526	0.0296	-0.7550	-0.1156	0.0307	-0.0621
Israel to PIJ Hostility2	0.0002	0.0001	0.0008	0.0042	0.0108	0.0890	0.0018	0.0000	0.0195	0.0038	0.0002	0.0022
Israel to Lebanon Hostility	**0.0410****	**0.0386****	**0.0495****	**0.1135***	**0.0988****	0.4038	**0.0604*****	**0.0492*****	0.0196	**0.0541****	**0.0407****	0.0282
Israel to Palestine Hostility	**-0.0059****	**-0.0059****	-0.0066	0.0053	-0.0141	0.6081	**-0.0089****	**-0.0050***	0.0562	-0.0049	**-0.0069****	0.0031
Good Sentiment to PIJ			**0.7981***	0.0524	**-0.3926***	-1.0406	**0.6917*****	**0.1073***	0.0795	-0.0172	0.0008	0.0235
Good Sentiment to Israel		0.0014	**-0.0070***	**-0.0042***	**-0.0175***	-0.1794	**-0.0293****	-0.0003	0.0000	**-0.0029***	-0.0003	0.0001
Constant	0.7605	0.2603	-0.6739	5.7278	7.2460	5.4013	0.5142	-0.4039	-14.0616	2.3630	1.5056	-1.7281
N	84	83	49	42	46	25	69	81	39	62	84	42
Percent Correctly Predicted	83.33	81.93	85.71	92.86	91.30	100.00	81.16	80.25	94.87	85.48	79.76	80.95
Percent Positives Correct	93.33	93.22	91.89	100.00	97.30	100.00	90.00	89.83	100.00	95.83	90.00	90.91
Percent Negatives Correct	58.33	54.17	66.67	66.67	66.67	100.00	57.89	54.55	71.43	50.00	54.17	44.44

Table 22: Palestinian Islamic Jihad Sentiment Models: Bad Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Al Aqsa to Israel Hostility	0.0012	0.0032	-0.0101	-0.1885	-0.0632	-2.0953	-0.0081	-0.0336	-0.1890	-0.0251	-0.0141	-0.0396
Hamas to Israel Hostility	0.0188	0.0181	0.0026	0.0094	-0.0207	-1.2639	0.0226	0.0235	-0.0128	0.0260	0.0219	-0.0132
Hezbollah to Israel Hostility	0.0119	0.0119	0.0346	0.0512	0.0237	0.4417	**0.0304***	0.0101	0.0273	**0.0559***	0.0110	0.0441
Lebanon to Israel Hostility	0.9796	0.9843						0.9996			0.9206	
Palestine to Israel Hostility	0.0226	0.0237	0.0239	-0.0169	0.0409	1.7546	0.0254	0.0334	0.0782	0.0272	0.0266	0.0260
Israel to Al Aqsa Hostility	0.0044	0.0053	0.1127	0.2478	0.0999	3.4989	0.0304	0.0128	0.1216	0.0460	0.0088	0.1015
Israel to Hamas Hostility	0.0002	0.0004	-0.0013	0.0067	0.0060	0.4828	-0.0016	-0.0039	-0.0025	-0.0062	-0.0027	0.0035
Israel to Hezbollah Hostility	**-0.0352***	**-0.0342***	-0.0242	**-0.0868***	-0.0406	0.0404	-0.0259	**-0.0345***	-0.0194	**-0.0463***	**-0.0376***	-0.0270
Israel to PIJ Hostility	0.0297	0.0287	-0.0447	0.1039	-0.1569	-4.7548	-0.0260	0.0173	-0.2249	-0.0047	0.0258	-0.1055
Israel to PIJ Hostility2	0.0002	0.0002	0.0015	-0.0025	0.0046	0.0826	0.0010	0.0003	0.0067	0.0002	0.0003	0.0034
Israel to Lebanon Hostility	**0.0410****	**0.0403****	**0.0540****	0.0630	0.0511	-0.1045	**0.0356****	**0.0451****	0.0061	**0.0713****	**0.0430****	0.0356
Israel to Palestine Hostility	**-0.0059****	**-0.0060****	-0.0067	0.0059	0.0040	0.4662	**-0.0060***	**-0.0050***	0.0285	-0.0046	**-0.0048***	0.0018
Bad Sentiment to PIJ			**0.2472***	**0.0560***	-0.0086	-0.6350	0.0539	0.0273	0.0112	**0.1641****	0.0006	0.0542
Bad Sentiment to Israel		-0.0002	-0.0017	-0.0012	-0.0033	-0.0669	-0.0024	0.0004	0.0004	-0.0006	0.0001	0.0005
Constant	0.7605	0.7531	-0.6807	0.9936	0.8378	14.0894	0.2923	-1.4210	-9.0496*	-2.2278	-1.3217	-2.8204
N	84	83	49	42	46	25	69	81	39	62	84	42
Percent Correctly Predicted	83.33	81.93	85.71	90.48	89.13	100.00	78.26	81.48	92.31	85.48	84.52	78.57
Percent Positives Correct	93.33	91.53	94.59	96.97	97.30	100.00	90.00	89.83	96.88	93.75	90.00	87.88
Percent Negatives Correct	58.33	58.33	58.33	66.67	55.56	100.00	47.37	59.09	71.43	57.14	70.83	44.44

Table 23: Palestinian Islamic Jihad Aggregated Sentiment Model

	Base	Sentiment
Al Aqsa to Israel Hostility	0.0012	-0.0193
Hamas to Israel Hostility	0.0188	0.0227
Hezbollah to Israel Hostility	0.0119	0.0234
Lebanon to Israel Hostility	0.9796	0.9270
Palestine to Israel Hostility	0.0226	0.0252
Israel to Al Aqsa Hostility	0.0044	0.0106
Israel to Hamas Hostility	0.0002	-0.0038
Israel to Hezbollah Hostility	**-0.0352***	**-0.0431***
Israel to PIJ Hostility	0.0297	0.0090
Israel to PIJ Hostility2	0.0002	0.0001
Israel to Lebanon Hostility	**0.0410****	**0.0640*****
Israel to Palestine Hostility	**-0.0059****	**-0.0074****
Good Sentiment to PIJ		**2.7791*****
Good Sentiment to Israel		**-1.7742***
Constant	0.7605	1.1821
N	84	84
Percent Correctly Predicted	83.33	88.10
Percent Positives Correct	93.33	93.33
Percent Negatives Correct	58.33	75.00

Table 24: Hezbollah Sentiment Models: Good Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Al Aqsa to Israel Hostility	0.0371	0.0416	0.8170	1.6100	-0.0089	13.5572	0.0426	0.0477	8.7069	0.0442	0.0655	0.2168
Hamas to Israel Hostility	0.0164	0.0145	0.8675	1.9125	0.0364	15.2936	0.0166	0.0165	-0.8417	0.0165	0.0190	0.2023
PIJ to Israel Hostility	0.0100	0.0050	0.2501	0.0649	0.0648	8.9681	0.0154	0.0113	10.8515	0.0073	0.0046	-0.0031
Lebanon to Israel Hostility	**0.5375***	**0.5351***	8.6861	14.2034	1.2281	199.8263	0.6628	**0.5342***	157.3826	**0.5456***	**0.5665***	3.5731
Palestine to Israel Hostility	-0.0043	-0.0025	-0.7086	-0.8799	-0.0475	-3.1615	-0.0059	-0.0089	1.4353	-0.0027	-0.0019	0.1873
Israel to Al Aqsa Hostility	0.0066	0.0093	0.5349	1.7198	**0.1115***	-6.3554	-0.0314	-0.0008	6.8331	0.0044	0.0087	0.3796
Israel to Hamas Hostility	**-0.0071***	-0.0062	-0.0330	-0.1130	-0.0092	-9.6505	**-0.0085***	-0.0065	-0.1211	-0.0059	-0.0032	-0.0752
Israel to Hezbollah Hostility	-0.0158	-0.0202	0.3354	1.9074	0.0379	-50.6709	-0.0424	-0.0197	-33.3545	-0.0200	-0.0115	0.0538
Israel to Hezbollah Hostility 2	0.0004	0.0005	-0.0023	-0.0135	-0.0003	0.7376	0.0006	0.0005	0.4575	0.0005	0.0004	0.0015
Israel to PIJ Hostility	0.0077	0.0112	-0.1023	-0.0825	0.0345	-9.5976	0.0135	0.0100	8.6755	0.0102	0.0198	0.1373
Israel to Lebanon Hostility	0.0039	0.0033	0.2197	0.1240	0.0172	16.6195	0.0057	0.0065	5.7469	0.0052	0.0034	0.0566
Israel to Palestine Hostility	**0.0136*****	**0.0139*****	0.0524	0.1589	**0.0282****	3.2194	**0.0161*****	**0.0136*****	2.0977	**0.0130*****	**0.0106****	0.0348
Good Sentiment to Hezbollah		-0.0037	0.3763	0.5097	0.0830	1.3298	**0.1160***	-0.0002	1.9007	0.0011	0.0025	0.0995
Good Sentiment to Israel		0.0002	-0.1526	-0.0943	**-0.0289***	-0.3820	**0.0178***	-0.0007	-0.3185	-0.0005	**-0.0011****	-0.0137
Constant	-5.3639***	-5.5579***	-43.8474	40.8248	-7.9133**	-806.0836	-7.0233***	-4.2541**	-482.4931	-5.4618***	-2.3318	-36.5046
N	84	83	56	49	53	32	78	81	46	70	84	49
Percent Correctly Predicted	86.90	87.95	92.86	100.00	96.23	100.00	88.46	86.42	100.00	84.29	88.10	95.92
Percent Positives Correct	86.96	88.89	90.48	100.00	95.24	100.00	90.00	86.05	100.00	78.13	86.96	93.33
Percent Negatives Correct	86.84	86.84	94.29	100.00	96.88	100.00	86.84	86.84	100.00	89.47	89.47	97.06

Table 25: Hezbollah Sentiment Models: Bad Sentiment

	Base Model	Ahram	Al Arabiya	Al Ayyam	Al Liwa	Al Manar	Al Yaum	Dar al Hayat	Hayat Jadid	Mustaqbal	Qudsway	Syria News
Al Aqsa to Israel Hostility	0.0371	0.0285	0.0944	2.0989	0.0170	1.0940	0.0427	0.0386	0.1794	0.0431	0.0504	0.0200
Hamas to Israel Hostility	0.0164	0.0224	0.1336	1.4642	0.0480	25.0752	0.0178	0.0176	0.0302	0.0204	0.0148	0.0702
PIJ to Israel Hostility	0.0100	0.0129	0.1022	2.2860	0.0540	28.5485	0.0214	0.0119	0.2780	0.0084	0.0123	0.0532
Lebanon to Israel Hostility	**0.5375***	**0.5786***	2.1083	47.3020	0.9108	459.6405	**0.6506***	**0.5688***	3.2957	**0.5654***	**0.5581***	1.5209
Palestine to Israel Hostility	-0.0043	-0.0040	-0.0821	-1.3040	-0.0439	6.8050	-0.0159	-0.0066	-0.0584	-0.0075	-0.0040	0.0115
Israel to Al Aqsa Hostility	0.0066	0.0016	**0.1693****	2.4333	**0.1092***	-14.8914	-0.0286	-0.0037	0.1624	0.0012	0.0104	**0.1515****
Israel to Hamas Hostility	**-0.0071***	-0.0064	-0.0105	0.2167	-0.0125	-21.6631	**-0.0089***	**-0.0076***	-0.0129	-0.0065	-0.0042	-0.0186
Israel to Hezbollah Hostility	-0.0158	-0.0094	0.1465	3.1783	0.0490	-71.4860	-0.0232	-0.0227	-0.3563	-0.0151	-0.0305	0.0899
Israel to Hezbollah Hostility 2	0.0004	0.0004	-0.0012	-0.0154	-0.0002	1.0718	0.0003	0.0005	0.0056	0.0004	0.0007	-0.0002
Israel to PIJ Hostility	0.0077	0.0066	0.0071	2.0363	0.0174	11.0610	0.0042	0.0099	0.1525	0.0127	0.0174	0.0420
Israel to Lebanon Hostility	0.0039	0.0053	0.0508	-0.0704	0.0174	39.9886	0.0047	0.0038	0.1432	0.0000	0.0077	-0.0036
Israel to Palestine Hostility	**0.0136*****	**0.0134*****	**0.0170***	0.3942	**0.0184****	6.8212	**0.0135*****	**0.0140*****	0.0476	**0.0125*****	**0.0126*****	0.0176
Bad Sentiment to Hezbollah		0.0374	0.0259	-0.1173	-0.0114	1.2450	**0.0637***	0.0002	-0.0291	0.0009	-0.0010	0.0206
Bad Sentiment to Israel		0.0011	**-0.0127***	-0.0502	0.0003	-0.2994	**0.0088***	0.0001	-0.0013	0.0003	-0.0002	-0.0029
Constant	-5.3639***	-6.2724***	-13.5957**	-70.9726	-9.3057**	-2090.0000	-6.5739***	-5.7545***	-19.0711	-6.2164***	-3.3340	-13.7199**
N	84	83	56	49	53	32	78	81	46	70	84	49
Percent Correctly Predicted	86.90	86.75	94.64	100.00	90.57	100.00	85.90	85.19	93.48	80.00	88.10	93.88
Percent Positives Correct	86.96	86.67	90.48	100.00	85.71	100.00	82.50	83.72	84.62	75.00	86.96	86.67
Percent Negatives Correct	86.84	86.84	97.14	100.00	93.75	100.00	89.47	86.84	96.97	84.21	89.47	97.06

Table 26: Hezbollah Aggregated Sentiment Model

	Base	Sentiment
Al Aqsa to Israel Hostility	0.0371	0.0386
Hamas to Israel Hostility	0.0164	0.0156
PIJ to Israel Hostility	0.0100	0.0124
Lebanon to Israel Hostility	0.5375*	0.5502*
Palestine to Israel Hostility	-0.0043	-0.0059
Israel to Al Aqsa Hostility	0.0066	0.0017
Israel to Hamas Hostility	-0.0071*	-0.0072*
Israel to Hezbollah Hostility	-0.0158	-0.0252
Israel to Hezbollah Hostility 2	0.0004	0.0006
Israel to PIJ Hostility	0.0077	0.0093
Israel to Lebanon Hostility	0.0039	0.0052
Israel to Palestine Hostility	0.0136***	0.0138***
Bad Sentiment to Hezbollah		-0.0014
Bad Sentiment to Israel		0.4504
Constant	-5.3639***	-5.1133***
N	84	84
Percent Correctly Predicted	86.90	88.10
Percent Positives Correct	86.96	89.13
Percent Negatives Correct	86.84	86.84

In Table 15 for example, we see that good sentiment toward Israel increased the probability of Al Aqsa entering a hostile phase in the Dar Al Hayat and Mustaqbal models. In Table 16, bad sentiment toward Israel also increased Al Aqsa's probability of becoming violent and bad sentiment toward the group appeared to decrease its probability of hostility. However, in Tables 21 and 22, both good and bad sentiment toward the Palestinian Islamic Jihad increased the probability the group would enter a hostile phase.

Two potential explanations emerge: PIJ responds to any sentiment by increasing its violent attacks, or "good" and "bad" sentiment are not necessarily interpretable without some additional context. We assume that good and bad sentiment toward groups of interest represent approval, satisfaction, or endorsement in the case of good sentiment and disapproval, dissatisfaction, or disaffection in the case of bad sentiment. However, groups may interpret sentiment expressed about them by these sources in other ways. For example, an attention seeking group may simply see any mention of the group by the press as publicity. We contend that dyadic sentiment data, sentiment expressed by one actor, directed toward another actor would be helpful in distinguishing between the kinds of sentiment a group might want and the kind of sentiment it might try to avoid.

The addition of sentiment variables in the Hamas models, shown on Tables 18, 19, and 20, reveal an effect of Israeli repression against Lebanon and the PIJ that did not show up in the original base model. In both cases, Israeli repression of the groups increases the probability of hostility by Hamas. Our aggregate measure only slightly improved the model's ability to correctly classify hostile and non-hostile phases though.

The sentiment models for both PIJ, shown in Tables 21-23, and Hezbollah, shown in Tables 24-26, look more impressive in that more variables turn out to be statistically significant predictors of those groups' hostility toward Israel. However, the models in general do not perform significantly better than the others. In Tables 21and 22, the Al Ayyam and Hayat Jadid models alone give us a good fit to the data. The models correctly classify 93 and 95% of hostile and non-hostile phases correctly. However, these results are somewhat misleading since those models are based on a relatively low number of observations. The lack of sentiment data available from those sources and random missingness in the data leave only about 40 observations for each model.

In terms of overall model fit, for Al Aqsa, The Dar al Hayat models appear to be the best good and bad sentiment models because of their ability to classify more of the negative cases correctly (65% and 59%, respectively compared to 25% in the base model). Both models (Table 15 and 16) fit the data better than the aggregate sentiment model (Table 17). For Hamas, The Ahram good sentiment model fit the data best (Table 18), while the Ahram bad sentiment model fit the data almost as well (Table 19). Both models fit the data better than the aggregate model (Table 20). For PIJ, the Qudsway bad sentiment model performed better than any of the other good or bad sentiment models. However, the best model of the PIJ data is the aggregate model. It classifies 88% of the cases correctly and classifies 75% of the negative cases correctly. As for Hezbollah, the Qudsway good and bad sentiment models outperform all the other good and bad sentiment models as well as the aggregate model. In fact, the Qudsway good and bad sentiment

models (Tables 24 and 25) are the best fitting models of all the groups' models good, bad, and aggregate.

Finally, we turn our attention to in-sample and out-of-sample forecasting. The models we have shown represent the best fitting models we found for each group using the available data. We used the best models using aggregate sentiment measures to make our in-sample and out-of-sample predictions which is discussed in the following section.

5.5 In-Sample and Out-of-Sample Forecasting

We chose the best aggregated sentiment models for each group of interest. While the models using aggregate sentiment measures did not "outperform" other models, they did have the advantage of offering us longer periods of sentiment data with which to model. The model used for Al Aqsa in-sample and out-of-sample forecasting is reported in Table 17. The model uses an aggregate measure of bad sentiment toward the group of interest. Figure 60 shows that the in-sample prediction from the model performs quite nicely. To show how these predictions play out over time, we devise bar graphs showing the actual violent phase points as well as the predicted violent phase points along a time series plot. A hostile phase *point* is a data point indicating violent activities during a hostile phase. The blue bars in the figures below show the actual hostile phase points, while the red bars illustrate predicted hostile phase points. When a red bar is stacked on top of a blue bar, the model correctly predicted the actual hostile phase data point (true positive). A blue bar by itself reveals where the model failed to predict a hostile phase point but there actually was such a hostile phase ongoing at that time (false negative). A red bar with no blue bar reveals where the model predicted a hostile phase point that did not occur (false positive). No bar indicates that the model did not predict a hostile phase point and there was no hostile phase point (true negative). The Al Aqsa in-sample seems to pick out the prolonged periods of hostility, anticipating the campaigns of violence by one or two months in some cases.

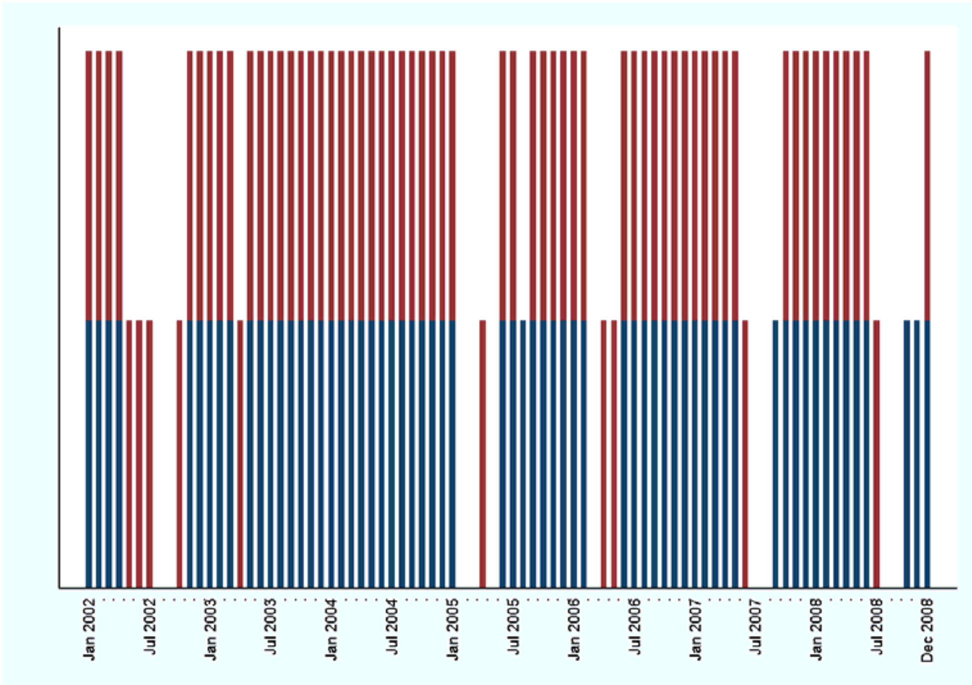


Figure 60: Al Aqsa Model

The out-of-sample forecast for Al Aqsa hostility, presented in Figure 61, indicates that the model had a little trouble distinguishing the duration of hostile phases. However, the model performed adequately at finding the onset of hostility. The three month non-hostile period beginning in June 2007 apparently saw decreased hostility between Al Aqsa and Israel, as Israel acquiesced to pressure to release a number of Al Aqsa prisoners.

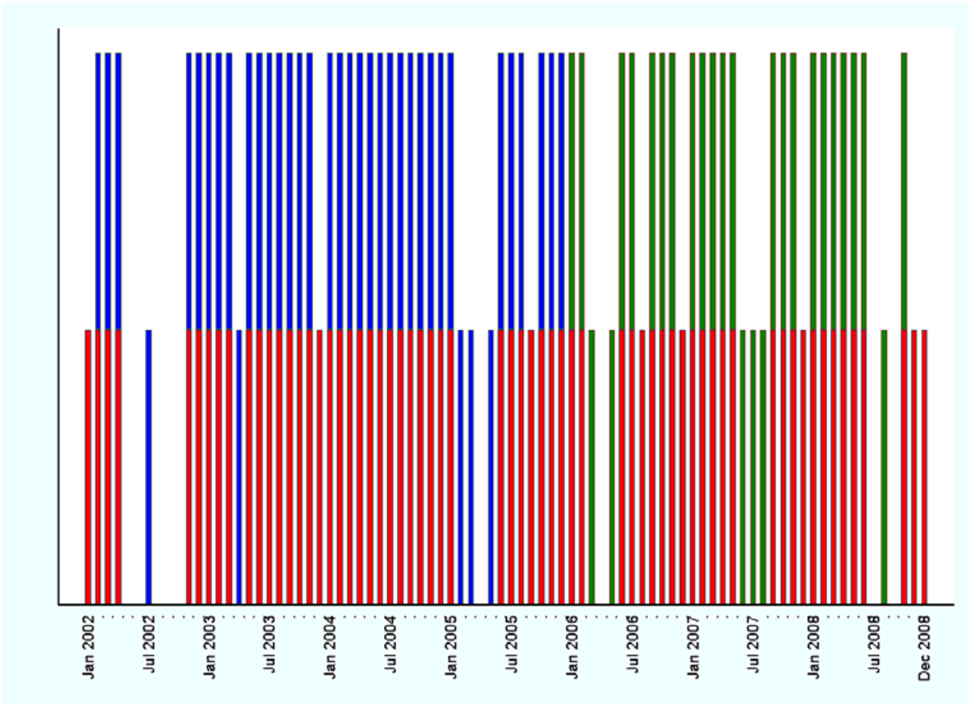


Figure 61: Al Aqsa Out-of-Sample Forecast

As mentioned earlier, Hamas appear to be engaged in hostility almost continuously. The model used for in-sample and out-of-sample forecasting is reported in Table 20 and uses an aggregate measure of bad sentiment toward the group.

Despite the fact that the group is almost always violent, the model does pick up on the infrequent periods of non-hostility. Figure 62 shows that our model picks up on the onset and cessation of hostile activity by Hamas. Figure 63 shows similar results, however the out-of-sample forecast does a poor job when it comes to the duration of the conflict which begins in October 2007.

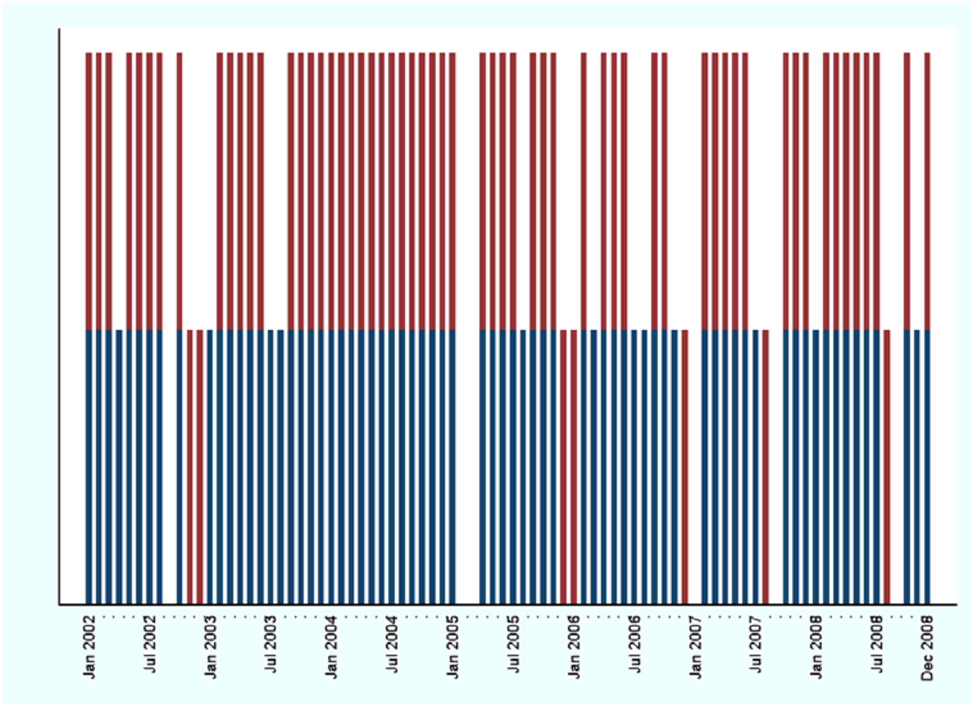


Figure 62: Hamas Model

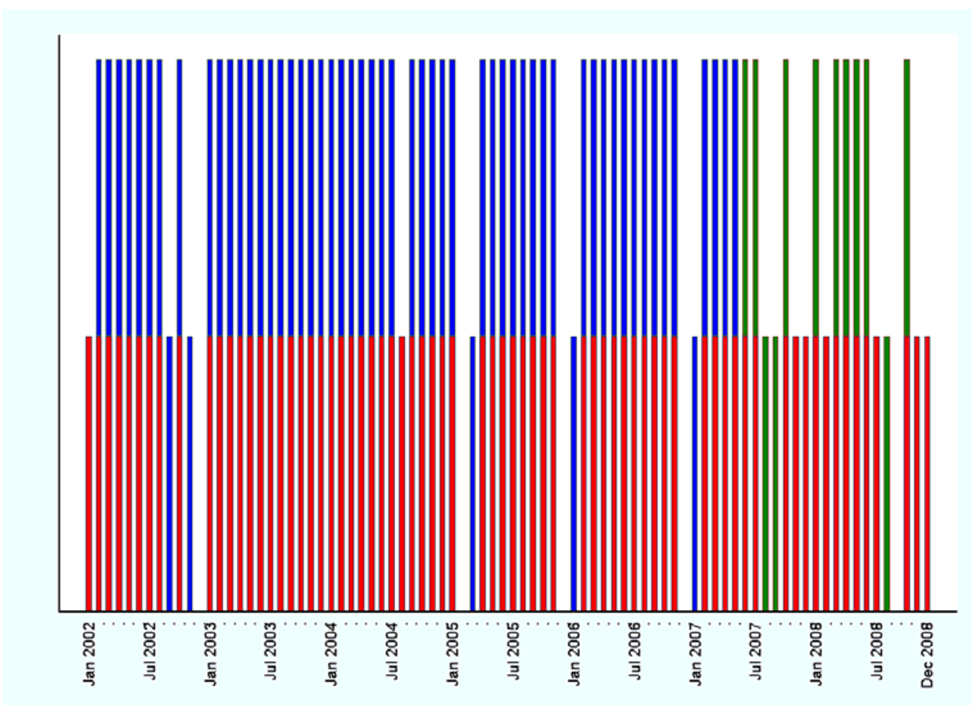


Figure 63: Hamas Out-of-Sample Forecast

Figures 64 and 65 present in-sample and out-of-sample model predictions for Hezbollah hostility. The model used for in-sample and out-of-sample forecasts for Hezbollah is reported in Table 26 This model uses an aggregate measure of bad sentiment toward Hezbollah.

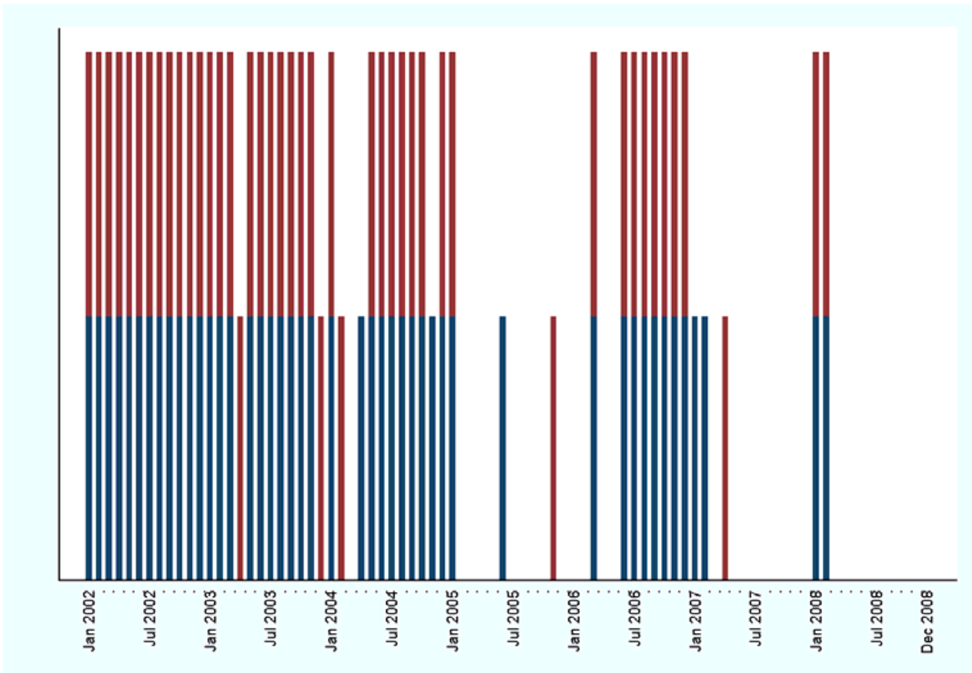
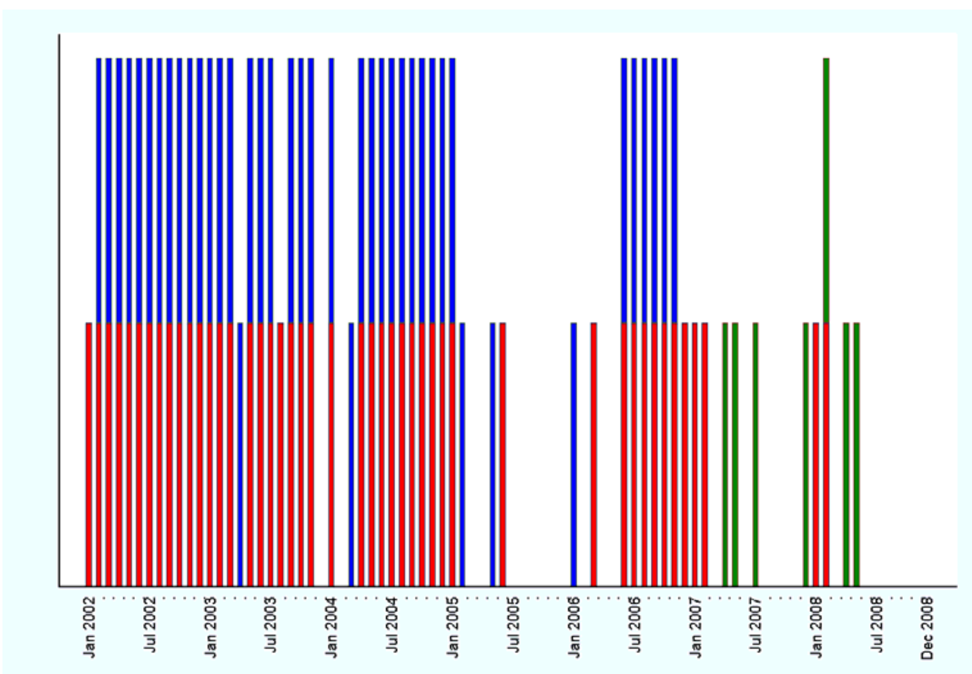


Figure 64: Hezbollah Model



Note: Out-of-sample forecast began on July 2005.

Figure 65: Hezbollah Out-of-Sample Forecast

Because hostile phases tapered off in the last half of the time period, we changed the cut-off date to January 2007 for the out-of-sample forecast. The in-sample prediction correctly classifies the major outbreaks of violence. And our forecast anticipates the brief hostile period beginning in January 2008.

Figures 66 and 67 present in-sample and out-of-sample model predictions for Palestinian Islamic Jihad hostility toward Israel. The model used for these forecasts is reported in Table 23 and uses an aggregate measure of good sentiment. The PIJ was almost always coded as being in a hostile phase toward the end of the series and the model largely picks up on that continuing trend in both the in-sample and out-of-sample forecasts.

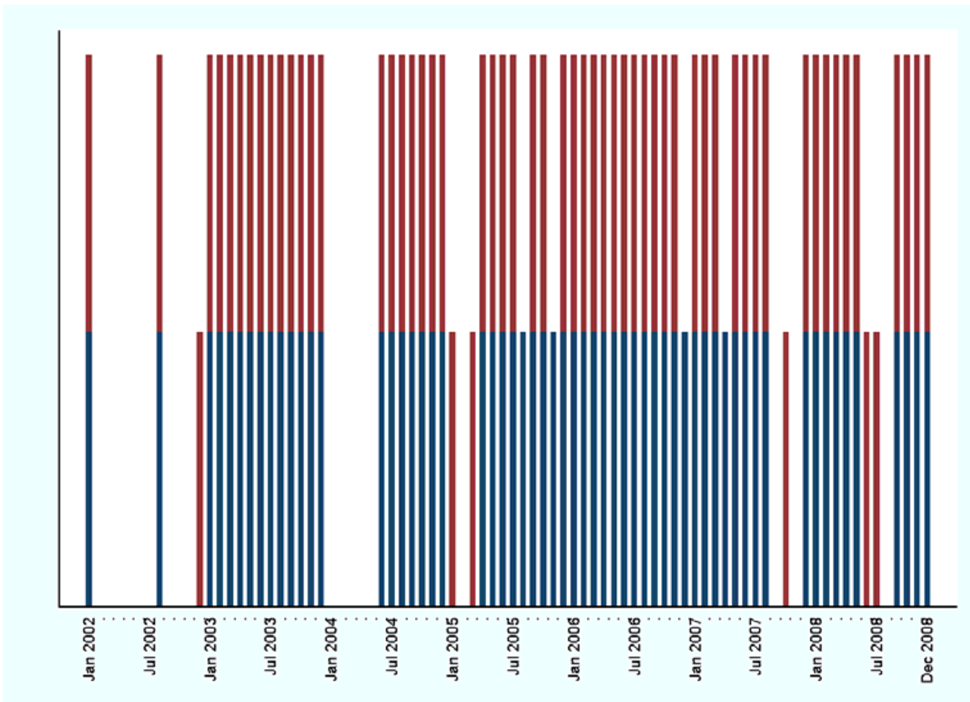


Figure 66: Palestinian Islamic Jihad Model

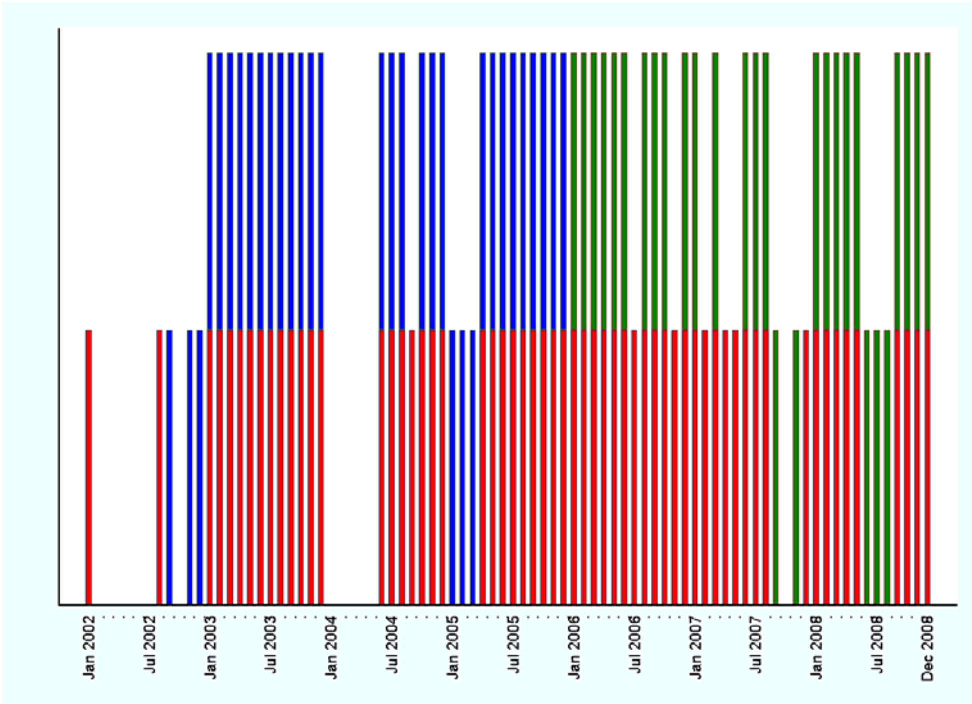


Figure 67: Palestinian Islamic Jihad Out-of-Sample Forecast

5.6 Discussion

Our task was to model the behavior of specific dissident groups operating in the Middle East: Hamas, Al Aqsa, Hezbollah, and PIJ. We sought to develop models to explain and forecast sustained periods of dissident violence against Israel. SSA collected new event and sentiment data through natural language processing techniques. Using this data, we specified models of group behaviors.

The addition of sentiment variables in some cases helps to explain the dynamics of conflict in the Middle East. However, there is much more work to do beginning with more comprehensive collection of sentiment and event data. In order to understand sentiment and how it may influence ongoing political conflicts, we must understand the goals and motivations of the source of sentiment, and consider whether the sources of sentiment are biased or represent widely held views. In effect, we need to know whether we should treat sentiment from an individual source as impartial or as favoring one side in a political conflict. In models of political conflict like the ones presented in this research, dyadic sentiment expressed by groups of interest toward other groups in the models could be useful in pinpointing the onset and cessation of hostility. Words may in fact precede actions. However, we're not convinced that this naively collected sentiment data can test this hypothesis adequately.

The field of automated content analysis is growing and technologies are being developed every day to extract meaningful information from texts. Many researchers who do textual analysis regard bag-of-words, which is simple counts of words, to be an industry standard. However, the

approach lacks context. On the other hand, dyadic sentiment data that records who is saying what about whom, puts sentiment into a meaningful context. SAE has shown that dyadic sentiment is useful in modeling group behaviors, particularly the ebb and flow conflict between groups.

That said, even this naïve approach yields some interesting results. For instance we learned that sentiment does not appear to affect each group in a similar manner. Some groups respond to negative or positive sentiment. Some groups increase hostility when sentiment is on their side, while others ramp up violence when it's not. The addition of sentiment variables improved our ability in some cases to explain and forecast political conflict. That said, there are a slew of results here and many are inconsistent with each other. It is hard to derive specific patterns across groups, sources, and measures. As such, we think more nuanced event and sentiment data would be useful to pursue in the future. We contend that the quality of data and how it is collected and measured will pay huge dividends in our abilities to test the sentiment hypotheses we generated for this study.

6.0 DATA APPENDIX

Foreign Direct Investment (FDI): investment of foreign assets in domestic structures, equipment, and/or organizations/businesses. FDI does not include foreign investment in a country's stock market. We obtained this measure from the World Bank Development Indicators Database.

Food CPI: Consumer Price Index of food items bought by a typical consumer used as a proxy for cost-of-living.

Government Repression: We scaled all of the government's hostile activities towards the GOI or the competing group(s) found in our events data using the CAMEO scale.[22] We then totaled only the negatively signed (i.e., hostile) values for each month. Finally, we multiplied the variable by -1 to generate a positively scaled variable.

Hostility: Hostility refers to all negatively signed CAMEO events summed by each month for the relevant actor. It is the same measure as government repression except the actor is not the government. Instead the measure may refer to another competing dissident group's hostile actions.

Political Terror Scale: The PTS is available for the years 1976-2008 and is a standards-based measure of the extent to which a government violates the physical right to integrity of the person. Violations are coded on a 5-point scale where higher values are associated with greater levels of violation. A score of one indicates a country where rights are respected (political imprisonment, torture, and extra-judicial execution are extremely rare). At the other end of the scale, a score of five indicates a country where the entire population is at risk to political imprisonment, torture, and extra-judicial execution as the state regularly employs all of these tactics as a means of rule. A value of four is assigned to countries where political imprisonment, torture, and extra-judicial killings are routine, but are only employed against those active in politics. A score of three indicates a state that routinely uses political imprisonment and extra-judicial execution occurs, but it is not endemic. Finally, a value of two represents states that employ a limited use of political imprisonment, but largely avoid torture, and rarely resort to political killing. The data are collected via content analysis of two sources: Amnesty International annual reports and the US Department of State's annual reports on human rights. Two different variables are created, one based on the Amnesty International coding and one based on the State Department coding. We report the findings using the State Department indicator.

Societal Sentiment towards the Government: a measure roughly equivalent to public opinion polling capturing societal attitudes toward government. It is measured on a Likert-like scale from -10 to +10.

Societal Sentiment towards Dissidents: a measure roughly equivalent to public opinion polling capturing societal attitudes toward dissident groups. It is measured on a Likert-like scale from -

[22] See http://web.ku.edu/~keds/cameo.dir/CAMEO.SCALE.txt for information on the scale and its values.

10 to +10, where +10 is extreme support for the actor or actor's policies and -10 is extreme disliking of the actor or actor's policies. .
Unemployment Rate: percent unemployed as per the International Labor Organizations LABORSTA database: http://laborsta.ilo.org/.

Violence or *Violent Events*: We collected only the violent events from our event data such as riots, armed clashes and attacks, suicide attacks, bombings, etc. and summed for the relevant actor for each month. For example, *GAM violent events* is all violent events carried out by GAM in a given month. *Other separatist groups' violent events* include all violent events carried out by all other relevant separatist groups excluding the GOI.

Many additional structural variables were tested in various models not reported here.

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LIST OF ACRYONMS

AFP	Agence France Presse
BCL	Bangladesh Chhatra League
BNP	Bangladesh Nationalist Party
BoWs	Bag of Words
CAMEO	Conflict and Mediation Event Observations
CAPES	Cascading Air Power Effects Simulation
COIN	Counterinsurgency
COPDAB	Cooperation and Peace Data Bank
DARPA	Defense Advanced Research Projects
DIME	Diplomatic, Informational, Military, and Economic
FDI	Foreign Direct Investment
FM	Field Manual
FUNCINPEC	Front Uni National pour un Cambodge Independant, Neutre, Pacifique et Coopratif
GAM	Free Aceh Movement
GDP	Gross Domestic Product
GNP	Gross National Product
GOIs	Groups of Interest
GRE	Graduate Record Exam
IDEA	Integrated Data for Events Analysis
IPI	Intranational Political Interactions
IRT	Item Response Theory
KEDS	Kansas Events Data System
KPNLF	Khmer People's National Liberation Front
LTTE	Liberation Tigers of Tamil Eelam
MCC	Maoist Communist Centre
MDS	Multi-Dimensional Scaling
MILF	Moro Islamic Liberation Front
NA	Non Applicable
NPA	New People’s Army’s
NSF	National Science Foundation
OPM	Free Papua Movement (or Organisasi Papua Merdeka)
PACOM AOR	Pacific Command – Area of Responsibility
PANDA	Protocol for the Assessment of Nonviolent Direct Action
PCS	Project Civil Strife
PIJ	Palestinian Islamic Jihad
PMESII	Political, Military, Economic, Social, Infrastructure and Information Systems
PTS	Political Terror Scale
PWG	People’s War Group
ROC	Receiver Operating Characteristic
SAE	Strategic Analysis Enterprises
SSA	Social Sciences Automation

TABARI	Text Analysis by Augmented Replacement Instructions
US	United States
VICDP	Violent Intranational Conflict Data Project
WEIS	World Events Interaction Survey